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MAKING GOOD DECISIONS: AN ATTRIBUTION MODEL OF DECISION QUALITY IN DECISION TASKS

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DEDICATION

To mom and dad. Your love, support, humor, and mentorship by example are everything I needed to succeed. Thank you for providing them without limits.

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Words cannot describe the gratitude that I feel for everyone who helped me reach this incredible milestone. Mom, you and dad were my rocks throughout the process, and you continue to support me regardless of the crazy things I get myself into. To “The Niese Girls”, Jennifer, Susan, and Vanessa, I would be lost without you. You’re my role models and my heroines.

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ABSTRACT

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Decision-makers endeavor to obtain the decision quality which puts them in a position to reach their goals. In order to control or influence decision quality, the processes by which individuals form their beliefs must be understood. In addition, many decision makers rely on decision support technologies to help find patterns in data and make sense of the input, so these technologies must be considered in parallel with the processes.

There have been numerous studies conducted to illuminate the factors which affect decision quality, however, many of these studies focused on objective measures and factors. This approach ignores individual perception, belief, and judgment. The evaluation of decision quality as perceived by the decision maker is important because these perceptions will direct future processes, decisions, and actions of the decision-makers. Also, by considering the perspective of the decision maker, theory and practice are being brought closer together. The focus of this study is to understand which factors contribute to individual's perceptions of decision quality by combining a priori and observation-based methods through a theoretical lens. Attribution theory is a well-established theory often applied when researching individual perception and serves as the foundation for the proposed model. The model examines the impact of the environmental attributes of task-technology fit and internal aspects of the decision-maker including intolerance for ambiguity and self-efficacy on decision quality.

This study empirically tested the proposed model using a two-phased approach. A pilot of 84 students was used to validate the instrument. The primary study of 413 business decision-makers who used decision support technology was used to validate the structural model. The model was validated using partial least squares structural equation modeling (PLS-SEM). Results show support that the perception of the fit between the decision support technology and the decision task directly affects decision-makers' perception of the resulting decision quality, as does the decision-makers' self-efficacy with decision making and with the decision support technology. Also supported is that task-technology fit and intolerance for ambiguity influence both self-efficacy with decision-making and with the decision support technology.

Keywords: Decision quality, attribution theory, decision support technology, decision support systems, task-technology fit, intolerance for ambiguity, self-efficacy.

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CHAPTER 1 INTRODUCTION

Decision-making is a fundamental activity for all individuals. Business decisions are those which involve comparative evaluation of alternatives within the confines of the decision-maker's role in an organization (Libby & Fishburn, 1977). In order to make informed decisions, input in the form of data must be considered. This data can come from within the company, via business transactions, from online sources, and from the decision or business environment (Franklin, 2013; Visinescu, Jones, & Sidorova, 2017; Yan et al., 2017). In today's environment, there is an increasing degree of expectation of individual decision-makers to understand the purpose of the task as well as how to fully understand and appropriately leverage decision support technology to quickly solve the decision tasks (McAfee & Brynjokfsson, 2012; Olfman, Bostrom, & Sein, 2006; Schrage, 2016).

Decision tools are designed to provide decision-makers with increased capability to extend their bound of rationality caused by their cognitive limits (Todd & Benbasat, 1999). Examples of such systems are decision support systems (DSSs) and big data analytics (BDA). The rules, algorithms, and methodologies these tools employ may vary greatly, and they will continue to evolve under new names and labels (Sallam et al., 2017), but their fundamental purpose will remain the same; to support business decision tasks. However, this purpose is not always achieved.

There is a high variability in the effectiveness of these tools (Davern, Shaft, & Te'eni, 2012; Poston & Speier, 2005; Speier & Morris, 2003). There is literature to support that decision support technologies are helping to improve decisions (Tan, Teo, & Benbasat, 2010). However, there is also literature to support that these same tools aren't making a significant impact, or that they can cause decision quality to decrease (Aldag & Power, 1986; Fuller & Dennis, 2009; Skitka, Mosier, & Burdick, 1999; Tan et al., 2010).

This variability needs to be understood because the use of these systems is continuing to increase. The demand for resources skilled in using decision support tools in the United States will soon be in excess of supply by 50% to 60% (Ovide, 2013). As supply grows to meet this demand, there will be more decision makers relying upon decision support technology to improve upon their decision quality. Without understanding the factors which impact decision quality, there is a higher chance that the resulting decision quality will be worse than if no decision support technology was used at all.

There are many reasons that decision makers increasingly leverage decision support technology despite the potential that they may not have an effect, or that they may have negative effects. Research has shown that individuals who leverage decision tools technologies increase their speed to insight, can increase their judgment consistency, and increase their accuracy (Glover, Prawitt, & Spilker, 1997; Wixom, 2013). Trade publications reported that decision-makers in top performing companies use decision tools five times more than low performers (Davern et al., 2012) and can make decisions at more than double the rate of lower performing companies (Lavalle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

The above outlined gaps in our knowledge limit our ability to successfully apply decision tools to improve decision quality and is therefore is deserving of close investigation. This study addresses the following research question in order to bridge these gaps; what are the causal factors of perceived decision quality assigned by individual decision makers in the context of business decision tasks when supported by technology?

Many decision quality studies to-date use objective measures of decision quality. In order to conduct research in this way, a “correct” answer must be known and identified which is used to compare to the actual answer and obtain the level of decision quality. A common method used is experiments. A sizable issue to using this method is that there are rarely “correct” answers in the real world because alternate decisions can’t often be deployed simultaneously so the “best” one can be determined. Also, the purpose of an experiment is to limit variables, but in the day-to-day of a business decision-maker, there may be numerous variables and ambiguity. For example, consider a plant scheduler who is creating the production schedule for the next month. The inputs to this decision involve aspects including the known demand for the products being produced, inventory levels, inventory costs, changeover costs (i.e. costs involved in changing machine settings to produce a different product), and the number of resources. However, the plant scheduler may also consider how she/he is incentivized; an incentive to maximize resource productivity will yield different decisions than an incentive to minimize cost.

A less-explored approach, and an alternative to the a priori method, is to let the decision-makers’ observations and experiences be the guide to determining the factors which are attributed to the decision quality. This method focused on the decision-maker’s judgments, beliefs and all of the inputs they considered to make the decision. The established theoretical tenets as well as the context of business decisions as supported by technology were considered to establish and support the research model. However, the point of view of the model was that of the decision-maker; how she/he observed and experienced the decision-making process and how she/he arrived at the outcome.

The intent of the proposed model is to uncover useful information to enable higher quality decisions. Decision quality is defined as the degree to which an individual believes that they made the best choice. The research endeavors to address decision quality in a holistic way, combining technology, the task, and individual cognition and rooting that model in individual perception and cognition. Only a few studies expand consideration of decision quality in a way that puts a magnifying glass on all three of these aspects. This is particularly important in the business context because of the significant number of variables, the level of uncertainty and the variation experienced in the industry in capitalizing on decision tools in the form of making better decisions (Chen, Preston, & Swink, 2015; Visinescu et al., 2017; Watson & Wixom, 2007).

Each theory has boundaries and limitations. This fact becomes especially problematic in environments which are ambiguous such as in decision-making tasks. This study looks for guidance from a combination of theories; TTF and attribution theory.

The purpose of this study is to investigate key factors which affect decision quality as perceived by decision-makers. The intent is to capture these perceptions in decisions they have already made so that they can consider the inputs, variables, and processes when evaluating decision quality. This process helps to bring theory and practice closer together, providing a clearer understanding of decision-makers states and beliefs. Attribution theory contains the boundaries, tenants, and assumptions needed to achieve these goals.

Attribution theory is concerned with the process of how each individual's perceptions and beliefs relate to their behavior (Heider, 1944; Hughes & Gibson, 1987). The process begins with an outcome and uses processes to assign a degree of success or failure as well as to determine causal factors of the outcome. Once an individual determines causation about their behavior or about observed behavior of others, they can take action to predict and improve the future outcomes (Kelley, 1967; Snead, Magal, Christensen, & Ndede-Amadi, 2015). Studies have shown that interventions into the attribution process can alter causal beliefs and alter achievement-related performance (Weiner, 2010). These findings indicate that as the level of knowledge of the attributes affecting decision quality and the process of how individuals attribute causal factors to decision quality increases, the level of control over decision quality also increases.

Attribution theory is a process which can be applied to any situation that individuals are attributing cause to an outcome. In the context of business decisions when the decision-maker is supported by technology, the degree to which that decision-maker believe she/he is supported by the technology is key. As a result, pulling in a theory which focuses on this belief facilitates the understanding of attribution in this context.

TTF was first conceptualized when Goodhue (1988) was looking for ways to connect technology and individual performance. TTF is often used to predict individual performance or systems use (Parkes, 2013). There is an aspect of user attitudes within the TTF model, but it is limited to how the individual feels about the task, the technology, the fit of task and technology, or system use. It is missing deeper and broader aspects of each individual such as cognition and personality which causes perception of a single event in numerous, different ways (Ariail, Aronson, Aukerman, & Khayati, 2015; Engin & Vetschera, 2017; Weiner, 1979). These different perceptions can stem from whether individuals perceive the event to have had a positive or negative outcome, the cause attributed to the outcome (e.g., ability versus luck), whether the cause was perceived as stable or unstable, internal or external to the individual, and the level of control the individual felt that they had (Heider, 1944; Kelley, 1967; Kelley & Michela, 1980; Weiner, 1979).

TTF is a construct which sheds light on how individuals create beliefs around technology which they use to support their tasks; in this case, their decision tasks. It is a process which considers aspects of the task and aspects of the functionality of the technology in order to determine the degree of belief that the technology is appropriate for helping them to complete their decision task. TTF cannot alone explain the process of how individuals attribute causal factors because it does not consider individual factors such as cognition and personality. In order to draw a more complete picture, the literature was reviewed and the factors of intolerance for ambiguity and self-efficacy were added. Intolerance for ambiguity and self-efficacy are highly relevant when operating within a business decision task context.

An individual's discomfort level with operating with a limited number of informational cues (intolerance for ambiguity) has been shown to affect how she/he acquires, stores, retrieves, and analyzes data as well as their pattern of thinking (Stella &

Malcolm, 2003; Zmud, 1979). All of these aspects could affect the process by which an individual attributes causal factors and determines the degree of decision quality.

Self-efficacy has been shown to affect the number and degree of challenges that an individual chooses to undertake, the amount of effort expended in an endeavor, and the level of perseverance in the face of difficulties (Wood & Bandura, 1989). These aspects also may affect the processes and outcomes of the attributional process.

The proposed research model was validated using a questionnaire developed with focus on the construct definitions and informed by existing instruments. The target respondents are business decision-makers who use decision tools to support their business decisions. There were two phases; a pilot phase with business students and a primary phase with business decision-makers. The pilot phase tested the instrument to ensure acceptable validity of all survey items and question clarity. The primary phase collected data to test the proposed model.

This research will make several contributions to both research and practice. It will extend the current understanding of how individual decision-makers form perceptions of decision quality which can be used to control those perceptions. It will also investigate factors which may affect decision quality, specifically TTF, tolerance for ambiguity, and self-efficacy in the context of business decisions. Lastly, it helps to bring theory and practice closer together to provide researchers with a better understanding of decision-makers' states and beliefs.

This research also may have implications for how managers lead individual decision-makers and how decision-makers approach decision tasks by providing empirical support for the idea that taking action to improve perceptions of TTF, intolerance for ambiguity, and self-efficacy can positively improve decision quality. Managers may find that implementing measures to improve awareness of decision tool functionalities and how those functions support decision tasks as well as measures to improve self-efficacy using the three lenses offered here. Lastly, managers may find that specifically evaluating aspects of an individual's tolerance for ambiguity and self-efficacy when hiring may result in employees who better fit into a decision-maker role.

This chapter built the case of the importance of the topic as well as the motivation for the research. Chapter 2 provides the current research on the topics relevant to this study. Chapter 3 uses the literature review as a foundation and guide to propose a theoretical model and a set of hypotheses. Chapter 4 discusses how the research will be conducted to test the hypotheses including the statistical methods and samples used. It also includes the analysis of the data. Chapter 6 discusses the results, limitations, and future research.

CHAPTER 2: LITERATURE REVIEW

The decision quality literature review was conducted by searching business and psychology databases for phrases such as “decision quality”, “decision performance”, and “decision satisfaction”. Then, decisions with the support of decision tools were searched for in the “basket of 8” journals include MIS Quarterly, Information Systems Research, Journal of MIS, European Journal of Information Systems, Journal of AIS, Information Systems Journal, Journal of Information Technology, and the Journal of Strategic Information Systems. They were used because they are considered the top journals in the IS field ("Senior Scholars' Basket of Journals," 2011). Decision Support Systems journal was also examined for studies meeting the same criteria because it is a top journal which contains publications relating to decision tools (Chen, Chiang, & Storey, 2012).

The literature review starts by explaining the approaches taken to date regarding decision quality. Much of the research on decision quality focused on the objective approach and little work focused on the subjective. The studies which have taken a subjective approach lack theoretical foundation.

This chapter explores a theoretical approach grounded in attribution theory to lay the foundation to study the factors which contribute to decision quality. Following a review of the foundation, a synthesis of the building blocks of self-efficacy, task-technology fit, and intolerance for ambiguity was provided. The chronological process explains the evolution of the history to the most current state of literature. Upon the conclusion of the literature review, the gaps were summarized.

Decision Quality Research Approaches

A decision is a choice among alternative options and based on information and analysis of that information, the decision-maker chooses the option which will maximize the value of the consequences (Balleine, 2007). Researchers tend to approach the study of decision quality in one of two ways; objectively and subjectively (perceived). Objective measurements tend to focus on which attributes actually impact decision quality. This approach must have a "correct" answer to compare actual answers so that the quality can be objectively measured and calculated. Subjective measurements tend to focus on which attributes individual decision makers perceive to have attributed to the resulting decision quality.

The perspective taken in the study is an important one because in the context of business decisions, the best answer is not always known so it is very difficult to obtain an idea of decision quality (Carneiro et al., 2019). When determining the quality of the decision, individuals typically consider the entire process, not just the decision itself (Higgins, 2000) which is fundamentally different than taking an objective measure of the decision quality.

Traditional research has focused on the objective measure of decision quality. Table 1 contains a summary of the studies which have used this objective approach. Also shown in the table is a lack of theoretical underpinnings to the research. Most use past literature to support their hypotheses.

Table 1

Decision Quality Objective Studies

Literature	Study Focus	Theory	Finding
(McIntyre & Ryans, 1983)	Decision Quality No DSS	No Named Theory	Task attributes influenced decision quality
(Cats-Baril, & Huber, 1987)	Decision Performance No DSS	No Named Theory	Variables tested impacted decision performance regardless of systems use in unstructured problems
(Taylor, 1987)	Decision Performance No DSS	No Named Theory	As goals became easier, decision performance marginally improved
(Iselin, 1988)	Decision Quality No DSS	No Named Theory	The relationship between the quantity of repeated dimensions and decision accuracy is an inverted U curve. Also, higher information diversity led to lower decision accuracy
(Sharda, et al., 1988)	Decision Quality DSS	No Named Theory	Access to a DSS significantly improves decision effectiveness
(Awasthi & Pratt, 1990)	Decision Quality DSS	No Named Theory	Providing incentives increased the time decision-makers spend on a decision, but did not impact the quality
(Chewning & Harrell, 1990)	Decision Quality No DSS	No Named Theory	Individuals who experienced information overload reached decisions of lesser quality
(Coll et al., 1991)	Decision Quality DSS	No Named Theory	Individuals leveraging a DSS took most time on the decision task, but did not make better decisions
(Todd & Benbasat, 1992)	Decision Quality DSS	No Named Theory	Individuals leveraging a DSS did not use more information than those without one
(Hahn, et al., 1992)	Decision Quality No DSS	No Named Theory	An inverted U-shaped function relating decision quality to information load occurred when time pressure was present, but did not when it was absent
(Kogut, & Phillips, 1994)	Decision Performance No DSS	No Named Theory	Individuals used sunk cost as a significant decision factor when positive returns were threatened

(Tuttle, et al., 1997)	Decision Choice No DSS	No Named Theory	Ethics have a strong effect on decisions
(Landsbergen et al., 1997)	Decision Quality DSS	No Named Theory	Individuals who leveraged expert systems made higher quality decisions but exhibited less confidence and commitment than did those who worked without an expert system
(Speier et al., 1999)	Decision Accuracy No DSS	Distraction/ Conflict Theory	Interruptions facilitate decision performance on simple tasks while hindering decision performance on complex tasks
(Raghunathan, 1999)	Decision Quality No DSS	No Named Theory	Decision performance can improve or degrade when information quality improves depending on the experience of the decision-maker
(Raghunathan, 1999)	Decision Quality DSS	No Named Theory	Individuals leveraging DSS made lower quality decisions than those without the DSS
(Hwang & Lin, 1999)	Decision Quality No DSS	No Named Theory	Information overload and underload have an adverse impact on decision quality
(Speier et al., 2003)	Decision Quality No DSS	No Named Theory	Decision performance was better when using text-based interface for low-complexity tasks and when using a visual interface for highly complex tasks
(Surinder & Cooper, 2003)	Decision Quality DSS	Media Richness Theory	Richer media can have significantly positive impacts on decision quality when participants' task relevant knowledge is high
(Poston & Speier, 2005)	Decision Performance DSS	No Named Theory	Ratings have a strong influence on KMS search and evaluation processes, which in turn affects decision performance
(MacLeod & Pingle, 2005)	Decision Performance No DSS	Aspiration Level Theory	Individuals who know what is attainable have higher decision performance, except when problem complexity is high

(Park, 2006)	Decision Performance DSS	No Named Theory	Using a full data warehouse resulted in significantly better performance than using a partial data warehouse. Using a partial data warehouse was not significantly better than not using a data warehouse at all
(Seo et al., 2007)	Decision Performance No DSS	No Named Theory	Feelings and emotions experienced during decision making can have positive effects on decision-making performance
(Williams et al., 2007)	Decision Quality DSS	No Named Theory	The use of a DSS did not improve decision quality
(Fuller et al., 2009)	Decision Quality DSS	Fit Appropriati on	Individuals using good-fitting technologies had better decision quality than those with poor-fitting technologies. After two days, individuals using the poor-fitting technologies matched those using good-fitting technologies
(Tan et al., 2010)	Decision Quality DSS	Resource-Matching Theory	When cognitive resources of the decision aids match those of the environment, decision performance is enhanced. If the system cognitive resources exceed or fall short of those demanded by the task, decision quality will degrade
(Chen et al., 2013)	Decision-making Errors No DSS	No Named Theory	Optimistic decision-makers (risk takers) tend to make Type II errors, whereas pessimistic decision makers (conservatives) tend to make Type I errors
(Starcke & Brand, 2016)	Decision Quality No DSS	No Named Theory	When under stress, decision-makers seek more rewards and take more risk than those in non-stress conditions, to the detriment of the decision quality
(Janssen et al., 2017)	Decision Quality DSS	No Named Theory	Big data analytics (BDA) supports improved decision quality
(Hardin, Looney, & Moody, 2017)	Decision Quality No DSS	No Named Theory	Credibility indicators can significantly influence decision-makers

Less focus has been on the subjective approach, as shown in Table 2. Similar to the objective studies, most do not apply theory to support the proposed hypotheses. This lack of theory limits the ability of the propositions to be consistent over various populations (Hair et al., 2016).

Table 2

Decision Quality Subjective Studies

Literature	Study Focus	Theory	Finding
(Aldag & Power, 1986)	Decision Quality DSS	No Named Theory	Adoption of decision support systems result in heightened decision confidence without corresponding improvements in decision quality
(Santhanam & Guimaraes, 1995)	Decision Quality DSS	No Named Theory	Decision support technologies would better support decision quality if they improved the support of communication, decreased the time to make a decision, and had increased ability to explore alternative strategies
(Ye & Johnson, 1995)	Decision Quality DSS	No Named Theory	Decision-makers would leverage decision support technologies more if the system provided justification for the results
(Yoon et al., 1995)	Decision Satisfaction DSS	No Named Theory	Decision satisfaction will be increased if increased training is provided and more focus is placed on a match between systems and tasks
(Amason, 1996)	Decision Quality No DSS	No Named Theory	Conflict can improve decision quality
(Carmeli et al., 2012)	Decision Quality No DSS	No Named Theory	When individuals learn from failures, decision quality is improved
(Meissner & Wulf, 2013)	Decision Quality No DSS	Behavioral Decision Theory	Scenario planning has a significant positive effect on decision quality
(Seo et al., 2013)	Decision Quality No DSS	No Named Theory	Individual absorptive capacity and perceived usefulness had positive effects on decision quality

(Xu et al., 2014)	Decision Quality No DSS	No Named Theory	Perceived enjoyment and product diagnosticity lead to better perceived decision quality and lower perceived decision effort
(Wood & Highhouse, 2014)	Decision Quality No DSS	No Named Theory	Careful decision-making can predict decision quality
(Chan et al., 2017)	Decision Performance DSS	No Named Theory	There is a mediating role of DSS use in the relationship between DSS motivation and decision performance
(Yan et al., 2017)	Decision Quality No DSS	No Named Theory	Self-efficacy in acquiring information is a key determinant for perceived decision quality
(Visinescu et al., 2017)	Decision Quality DSS	No Named Theory	Level of decision support technologies, problem space complexity, and information quality support higher perceived decision quality
(Carneiro et al., 2019)	Decision Quality No DSS	No Named Theory	Using cognitive and emotional measures increase the ability to predict perceived decision quality

When the scope of literature is tightened to those involving decision support technology, a range of outcomes can be observed. Some studies find that decision support technology improves decision quality (Janssen, van der Voort, & Wahyudi, 2017; Landsbergen, Coursey, Loveless, & Shangraw Jr, 1997; Sharda, Barr, & McDonnell, 1988) some find that these tools do not improve or degrade decision quality (Aldag & Power, 1986; Coll, Coll, & Rein, 1991; Todd & Benbasat, 1992), and some find that there are specific aspects which need to be in place to realize improved decision quality (Chan, Song, Sarker, & Plumlee, 2017; Fuller & Dennis, 2009; Park, 2006; Poston & Speier, 2005; Santhanam & Guimaraes, 1995; Surinder Singh & Cooper, 2003; Tan et al., 2010; Visinescu et al., 2017; Ye & Johnson, 1995; Yoon, Guimaraes, & O'Neal, 1995).

Attribution Theory

Attribution theory was originally developed by Heider (1944) who discussed the "attribution of a change to a perceptual unit" (p. 358) or, in other words, how individuals perceive causality of a change or event. He argued that attributing causes to actions is one way to give meaning to change. Hughes and Gibson (1987) defined attribution theory as a cognitive process involving perception and inference to deduce causation; a study of the rules of how people come to "know" what they see about other people and situations" (Hughes & Gibson, 1987). The purpose of attribution theory is to describe motivational conditions so that future behavior can be understood and predicted (Fishman & Husman, 2017; Forsterling, 2011; Kelley, 1967; Snead et al., 2015).

The focus of attribution theory is on the perceived causes of behavior, not on actual, objectives causes of behavior (Heider, 1944). These perceived causes of behavior are referred to as attributes. Attribution theory is often described as "psychology of the man on the street" (Forsterling, 2011, p. 3); that individuals use to understand, explain, predict, and control everyday events (Forsterling, 2011; Heider, 1944; Kelley & Michela, 1980). Individuals structure their own behavior and explain what goes on around them based on what they perceive.

There are two levels of attribution theories; attribution theories and attributional theories (Kelley & Michela, 1980; Weiner, 2010). Attribution theories are concerned with studying attributes such as contextual cues and personality traits that lead to outcomes, often labeled as causal explanations. In other words, studying attributes to determine how a respondent would explain them. For example, attributes to the causal factor of failing a test could include bad luck, a lack of ability, or having a poor teacher. Attributional theories are concerned with the psychological and behavioral consequences of attributions (Forsterling, 2011). A common method to capture these consequences is to ask survey respondents to determine an attribution for some event (e.g. failing due to lack of ability) then articulate their psychological or behavioral reaction (e.g. feeling anger or quitting that activity) (Forsterling, 2011).

This study's focus on the process individuals use to attribute causal attributes so attributional theories are out of scope. There are three primary attribution theories; Heider's Naïve Psychology of Attributes (1944), the Correspondent Inference Theory of Jones and Davis (1965), and the Attribution Theory of Kelley (1967).

Heider's model (1944) formalized ways in which individuals not trained in the scientific method or in psychology might try to understand behavior. It emphasized the perceiver's subjective experience rather than describing objective factors of the environment. Jones and Davis's model (1965) was drawn from Heider's, but emphasized the effects caused by an action. Kelley's model (1967) was also drawn from Heider's. It analyzed the covariation between potential causes and their effects. As such, the descriptions and attributional processes involved in this version are more objective in nature.

The outlined theories have a set of common assumptions which provide guidance on studying and applying them consistently. The first assumption is that behavior is determined in some way; that it is not random. Second, that that individual cognition affects how the perceiver interprets the stimuli and how behavior is altered as a result. Third, that humans are rational beings so some level of consistency can be reached. The final assumption is that all individuals see value in attempting to explain events and behaviors both inside themselves and in the external environment (Forsterling, 2011; Heider, 1944; Jones & Davis, 1965; Kelley, 1967; Kelley & Michela, 1980).

At a basic level, attribution theory starts with an outcome which is noteworthy. People generally do not exert the cognitive effort required to make cause attributions in everyday situations (Martinko, Harvey, & Douglas, 2007). Outcomes which are particularly important, surprising, or unexpected are common triggers for the attributional process (Weiner, 1985).

Attribution Theory as a Frame

The framework applied to this research is the attribution theory process, specifically, Heider's naïve psychology of attributes (Heider, 1944). This attributional theory was chosen over the correspondent inference theory (Jones & Davis, 1965) and the attribution theory of Kelley (1967) because of the focus on how average individuals (i.e. those without formal psychology training) determine causality. Specifically, because this model uses the perceptions of individuals (subjective aspects). The correspondent inference theory doesn't fit this study because their model focuses on the effects produced by an action. This study examined the process by which decision quality perceptions are formed; not on the actions taken after the attributions are determined or the effects of those actions. Kelley's model was not appropriate because it analyzes covariation between causes and effects which is more objective in nature.

Heider's naïve psychology of attributes uses attributes as inputs to determine the reason for the outcome. The point of this process is to determine the causal explanation of an event, an action, or a decision (Heider, 1944). The outcome in this study is the determination of the level of decision quality as perceived by the decision-maker. The attributions of the outcome are grouped into two categories, consistent with Heider's (1944) model; attributions residing in the environment and attributions residing in the person (decision-maker).

There are many attributes which individual decision-makers may attribute to decision quality. Numerous attributes have been studied in the literature. The context in which the decision is being made must be considered when determining which attributes to include in the model. The context in this study is business decision-making using technology to support those decisions.

Since the decision support technology is a key piece of the context, the degree to which the decision-maker feels that they are supported by the tools they are relying upon is a key concept. TTF captures this belief; it is defined as the degree to which an individual believes a technology fits the task at hand (Goodhue, 1988). TTF may affect the decision-maker's perception of their abilities and the effort she/he expends.

Bandura (1977) argued that behaviors are related to an aggregate of behavior/consequence patterns gathered by identifying patterns to determine necessary actions. As such, beliefs have a significant influence on behavior. One such belief is about one's own judgements regarding abilities, or self-efficacy. The various definitions often vary three aspects; specificity of the technology, of the task, and of the individual's skillset. In the context of IS, self-efficacy is often conceptualized as computer self-efficacy (Compeau & Higgins, 1995b; Johnson & Marakas, 2000; Marakas, Yi, & Johnson, 1998). Gupta and Bostrom (2019) argued that task was not adequately represented in the dyadic conceptualization of general and specific computer self-efficacies so they defined four types of self-efficacy which combines the level of technology (general or specific) and knowledge type (simple or complex). Consistently, this study conceptualizes two forms of self-efficacy; self-efficacy with the decision support technology and self-efficacy with decision-making.

A consideration when studying decision-making from an attribution theory perspective, is how the decision-maker perceives ambiguity which is a situation containing a lack of or conflicting informational cues (Budner, 1962). Tolerance for ambiguity is defined as the degree to which an individual feels threatened by ambiguity or ambiguous situations. Making decisions leveraging DSSs involves highly unstructured processes which creates an environment of ambiguity in which decision-makers must navigate. The way in which they respond may impact their causal attributions.

As mentioned, the two categories of attributions are environmental and internal to the decision-maker. Task-technology fit (TTF) is an aspect of the environment and intolerance for ambiguity and self-efficacy as aspects of the decision-makers.

Environmental Attributions – TTF

As highlighted in Heider’s naïve psychology of attributes, the two categories of causal factors are environmental and internal. The context of this study is business decision tasks made as supported by decision support technology. A popular way to analyze tasks and technologies in information systems literature is to apply TTF.

Task-technology fit was first conceptualized by Goodhue (1988) who was searching for a link between information systems (IS) and individual performance. He modified the theory of work adjustment (Goodhue, 1988) from the job satisfaction literature as the foundation to focus on IS use. The original theory of work adjustment explains why workers adjust to their work environments (Dawis, Lofquist, & Weiss, 1968). The new model of TTF showed that fit was created by marrying task requirements with IS functionality which then led to performance.

Goodhue then worked with Thomson to create and test the technology-to-performance chain (TPC) (Goodhue & Thompson, 1995) which Goodhue had referred to as system-to-value chain in his earlier paper (Goodhue, 1988). The premise of the TPC model is that in order for IS to have a positive effect on performance, it must be used and it must fit the task requirements as perceived by the user. This theory was tested using numerous industries using a variety of systems. The results showed strong support that TTF and utilization affect performance (Cane & McCarthy, 2009; Goodhue, 1995; Staples & Seddon, 2004).

Tan et al. (2010) executed a test which showed that when there was a fit between the amount of cognitive resources offered by the decision tool and the cognitive requirements of the task, that decision makers' decision outcomes were enhanced. However, when the decision tool rendered more cognitive resources than required by the task, decision-makers engaged less to the detriment of the decision outcome. When the decision tool rendered less cognitive resource than required by the task, decision-makers relied on simple heuristic decision strategies to the detriment of the decision outcome. This is further support of the idea of the value of TTF.

Parkes (2013) deconstructed TTF into three two-way interactions to determine how the interactions each affect user attitude and performance. A controlled laboratory experiment was used to uncover three interactions. They found that user attitudes were affected by the fit between individuals and technology, that technology performance was affected by the fit between task and technology, and that technology performance was affected by the fit between the task and the individual. Overall, the results showed that fit should be considered separately for each combination to examine the effects. Another interesting finding is that when there was a good fit between task and the individual, task performance improved, however, if technology was used, the performance decreased slightly. The author surmised that the individuals relied too much on the system recommendation which supports the issue that systems can cause effort minimization and cognitive laziness (Glover et al., 1997).

Internal Attributions – Self-efficacy

Bandura wrote the seminal piece on self-efficacy in 1977. His purpose was "to present an integrative theoretical framework to explain and predict psychological changes achieved by different nodes of treatment" (Bandura, 1977, p. 191). He defined self-efficacy as a feeling of confidence (or lack of confidence) in performing a behavior or task.

Bandura (1977) stated that although the common view was that behaviors are controlled by their immediate consequences and outcomes, he believed that behavior is related to an aggregate of behavior/consequence patterns. He theorized that individuals process feedback information which are gathered over time, identify patterns, then determine necessary actions to produce desired outcomes. Therefore, beliefs can have a significant influence on behavior. He went so far as to say that self-efficacy predicted behavior more strongly than outcome expectancies or past performance. Since then, there has been empirical evidence of this proposition. In an analysis of the research, Gist (1987) compiled the evidence which supports that self-efficacy was found to be a better predictor of behavior than past behavior and has also been found to affect one's choice of activities, skill acquisition, effort expenditure, initiation of behavior and persistence in the face of adversity. Further, those with low self-efficacy tend to engage in fewer coping efforts, give up more quickly, evidence less mastery, have lower efficacy in goal-setting, and seek less feedback.

In order to establish the relationship between behavior and outcomes, Bandura theorized that outcome expectations need to be established. Outcome expectancies are a person's estimate that a certain behavior will lead to a certain outcome as perceived by the individual. Although they may sound similar on the surface, outcome expectancy and efficacy expectations are not interchangeable. It's possible for individuals to believe that a course of action will produce an outcome (outcome expectancy), but if they don't feel that they can perform those activities (efficacy expectation) then the information will not influence their behavior.

The self-efficacy construct has been studied and measured as a stand-alone construct and has been separated into other constructs to better understand and predict behavior. It is important to clearly understanding the theoretical underpinnings of the definition of self-efficacy being tested so that the intended conceptualization can be properly defined and measured.

Self-efficacy has been conceptualized as general self-efficacy (Chen, Gully, & Eden, 2001; Sherer, Maddux, & Mercandante, 1982), social self-efficacy (Sherer, Maddux, & Mercandante, 1982), task self-efficacy (Chen et al., 2001; Sherer et al., 1982), computer self-efficacy (Compeau & Higgins, 1995b; Hill, Smith, & Mann, 1987), general computer self-efficacy (Agarwal, Sambamurthy, & Stair, 2000; Marakas et al., 1998), application environment computer self-efficacy (Marakas et al., 1998), application-specific self-efficacy (Marakas et al., 1998), and task-specific computer self-efficacy (Agarwal et al., 2000; Marakas et al., 1998).

General self-efficacy (GSE) is trait-like; as a belief developed over time across a wide variety of situations and contexts (Chen et al., 2001). Since GSE is an aggregate perception, it is more stable over time. Many researchers argue that GSE has little to no relation to self-efficacy beliefs related to a specific activity or behavior; because they are not "matched" (Chen et al., 2001; Thatcher & Perrewe, 2002). A common explanation in the literature is that GSE fails to predict behavior when it is not appropriately matched; that the generality or specificity of the efficacy construct measured is matched to the specificity or generality of the performance predicted (Chen et al., 2001).

This may explain why many studies have found task self-efficacy to predict outcomes well; because task self-efficacy is specific to the task being performed. As such, GSE has been shown to be a better predictor of general performance and task self-efficacy is a better predictor of specific task performance. When comparing the effectiveness of dynamic, malleable differences (e.g. computer anxiety), stable, situation-specific traits (e.g. personal innovativeness), and stable, broad traits (e.g. trait anxiety and negative affectivity), Thatcher and Perrewé (2002) showed empirically that situation-specific traits have a greater influence on situation-specific individual differences than do broad traits. Therefore, these measures cannot be substituted for each other and highlights the importance of clearly understanding the theoretical underpinnings of the definition of self-efficacy being tested so that the appropriate scale can be used to accurately capture it.

Similar to self-efficacy, computer self-efficacies often separated into task and general self-efficacies. Task computer self-efficacy is defined as relating to a specific task such as entering data into a spreadsheet and general computer self-efficacy is defined as a higher-level judgment of ability to apply their skills to a broad range of tasks (Agarwal et al., 2000; Compeau & Higgins, 1995a). Marakas et al. (1998) argued that the computer self-efficacy (CSE) construct had experienced highly contradictory evidence in the literature at the time of their article due to the lack of attention to interactions and confusion in the levels studied. They performed a literature review to highlight the weaknesses in existing measures and the level of control in the antecedents. Marakas et al. (1998) point out that there are many levels of CSE; general computer self-efficacy (judgment of efficacy across multiple computer application domains), application environment (operating system), application-specific (word processor, spreadsheet, decision tool), and task specific computer behavior (judgment on efficacy in performing a specific task such as making a decision using system support). They concluded that task-specific self-efficacy (judgment related to a specific task in a specific domain) and general computer self-efficacy (represents judgment developed over time and over cross-domain experiences) are unique and distinct theoretical constructs which cannot be treated interchangeably. As such, the constructs must also be depicted in theoretical models and measured separately in measurement models.

Similar to Marakas et al. (1998), Gupta and Bostrom (2019) conceptualized computer self-efficacy into four types derived from combinations of specificity (specific versus general) and the task type (simple versus complex). The types are specific technology and simple task self-efficacy (SS-SE), specific technology and complex task self-efficacy (SC-SE), general technology with simple task self-efficacy (GS-SE), and general technology and complex task self-efficacy (GC-SE). They argue that the more complex the task and the more general the technology, the more an individual relies on psychological confidence as opposed to actual skills. These constructs were shown to be empirically distinct.

Self-Efficacy as an Attribute

Self-efficacy has been shown to be an effective predictor. Outcomes of self-efficacy are typically grouped into beliefs (e.g. affect and ease of use) and behaviors (e.g. system use and early adoption) (Agarwal et al., 2000). Each implies different treatments and actions to encourage the “correct” self-efficacy.

Computer self-efficacy has been studied in terms of use. It has been found to have a positive relationship with individuals’ expectations of computer use, their emotional reactions to computers (affect and anxiety), their actual computer use, and to be positively influenced by the encouragement of others, as well as others’ use of computers (Compeau & Higgins, 1995a; Hill et al., 1987).

Since self-efficacy has been shown as a strong predictor of behavior, it has been used to create many insights into business-specific situations. Self-efficacy has been linked to performance in organizational and educations settings, job search, insurance sales, research productivity, adaptability to technology, coping with career related events, idea generation, managerial performance, skill acquisition, and adjustment to a new organization (Stajkovic & Luthans, 1998). Stajkovic and Luthans (1998) performed a study to synthesize and test the research specific to the relationship between self-efficacy and work-related performance to enable comparison across studies. They found that there was a significant positive relationship across many different methods and contexts.

An individual's perception of how abilities form also impact self-efficacy. Wood and Bandura (1989) state that if an individual understands their abilities to be an incremental skill that can be enhanced, then they can adopt a learning goal and expand on their current capabilities. Under a situation of failure, those with this perspective can view it as a learning experience and as a chance to improve and their self-efficacy. They will therefore likely not be negatively impacted by that failure. However, if an individual perceives ability as a fixed entity, then failures would be viewed as threatening and, as a result, he or she would reduce goals, prefer tasks that minimize errors, and would experience a negative effect on self-efficacy. In addition, when faced with roadblocks and difficulties, those who understand ability to be static tend to focus on their personal deficiencies and the issues can seem larger than what they are. Wood and Bandura (1989) conducted a study to test these points and found that those who performed challenging tasks under the conception of ability as a fixed entity experienced a negative impact on self-efficacy, lowered their goals, and became less efficient. Those who performed challenging tasks under the conception of ability as an acquirable skill maintained their level of self-efficacy, set more challenging goals, and were more effective in implementing strategies.

Internal Attributions – Intolerance for Ambiguity

There has been a great amount of cross-disciplinary interest in intolerance for ambiguity since its introduction in 1950 (Kirton, 1981). Tolerance for ambiguity and intolerance for ambiguity were both defined by Budner (1962). He defined tolerance for ambiguity as “the tendency to perceive (i.e. interpret) ambiguous situations as sources of threat” (p. 29) and tolerance for ambiguity as “the tendency to perceive ambiguous situations as desirable” (p. 29). Each has been studied and conceptualized, depending on which was a better fit for the context of the study. This study’s focus is on intolerance for ambiguity; therefore, the following sections will specifically refer to it.

There have been many studies which looked at various relationships involving intolerance for ambiguity. Intolerance for ambiguity has been found to have a negative relationship with internal locus of control (Furnham & Ribchester, 1995). The theory is that the individuals who believe a task is based on acquired skill (related to having an internal locus of control) are higher performers than those who believe that success is based on inherent ability (related to external locus of control) (Wood & Bandura, 1989). Intolerance for ambiguity has also been shown to have a negative relationship with job satisfaction (Furnham & Ribchester, 1995; Gallivan, 2004). Gallivan (2004) studied tolerance for ambiguity in the context of context analyzing job satisfaction when undergoing changes in job skills due to new technology. He found that tolerance for ambiguity contributes to job satisfaction more than the factors which normally explain it. Ambiguity in the workplace has been shown to increase stress which decreases job satisfaction, so the lower the intolerance for ambiguity, the higher the job satisfaction (Furnham & Ribchester, 1995). Gallivan (2004) had hypothesized that having a high tolerance for ambiguity would be positively related to high job performance. The data did not support that hypothesis, but the reason he posited was that the relationship existed but mediated through job satisfaction (which his data showed had a positive relationship with job performance).

Intolerance for ambiguity has also been found to determine how much information and the number of alternatives an individual is willing to consider (Schaninger & Sciglimpaglia, 1981). Searching for new information can lead to more questions and more ambiguity, so individuals with a high intolerance for ambiguity tend to identify and consider fewer cues and fewer alternatives (Dollinger, 1984). Schaninger and Sciglimpaglia (1981) supported this theoretically by turning to perceived risk theory which states that cognitive differences in individuals affect the amount of information sought and how well that infomration is processed. Vandenbosch and Huff (1997) found that a strong relationship between low intolerance for ambiguity and a predisposition toward scanning.

Chapter Summary

This chapter presented a literature review of decision quality and the factors which may have an effect on it. The review showed that there is limited subjective research from the decision-maker's point of view. It also showed that the extant research primarily draws from existing research as opposed to using theory as a foundation. Lastly, it showed that there is a high degree of consistency as to whether decision support technologies help or hinder decision quality.

The next chapter proposes a model to address these gaps. The model draws from attribution theory which considers the process by which decision-makers determine causality of an event and the resulting decision quality. This foundation is used to support the proposed causal attributes of TTF, intolerance for ambiguity, self-efficacy with decision-making, and self-efficacy with the decision support technology.

CHAPTER 3 MODEL DEVELOPMENT AND THEORY

This chapter presents and explains the research model as presented in Figure 1. It builds on the literature review findings and the gaps as identified in the previous chapter. First, an overview is presented, then the theoretical arguments are made for each relationship in the model. The chapter concludes with an overview of the way in which the model will be tested.

As mentioned, research using an objective approach to measure decision quality has been a popular method applied to understand the effectiveness of decision support technologies. This study argues that the decision makers are the best resources to determine the factors attributed to perceived decision quality. Therefore, the antecedents and theoretical underpinnings used in the proposed model reflect the point of view and beliefs of the decision maker through an attribution lens.

Attribution theory provides a structured view of how individuals determine the causal factors of decision quality when making unstructured decisions; it lends insight into psychological perception formation (Heider, 1944; Kelley & Michela, 1980; Weiner, 2010). Attribution theory also allows for the consideration of both internal and environmental factors. The research in the area of decision quality often uses highly structured experiments to determine the quality of the structured decisions (Chan et al., 2017; Meissner & Wulf, 2013; Xu et al., 2014). This approach does provide value, but not for business-related decisions which are often highly unstructured.

As described by Heider (1944), there are two categories which causal attributions fall into; environmental and internal. Since environmental factors are outside of the individual, she/he has limited control over them. These factors are observed by the individual and, if perceived as meaningful, can be critical in the attribution made by that individual (Shaver, 1983). Internal factors include an individual's personality, skill, and ability (Forsterling, 2011).

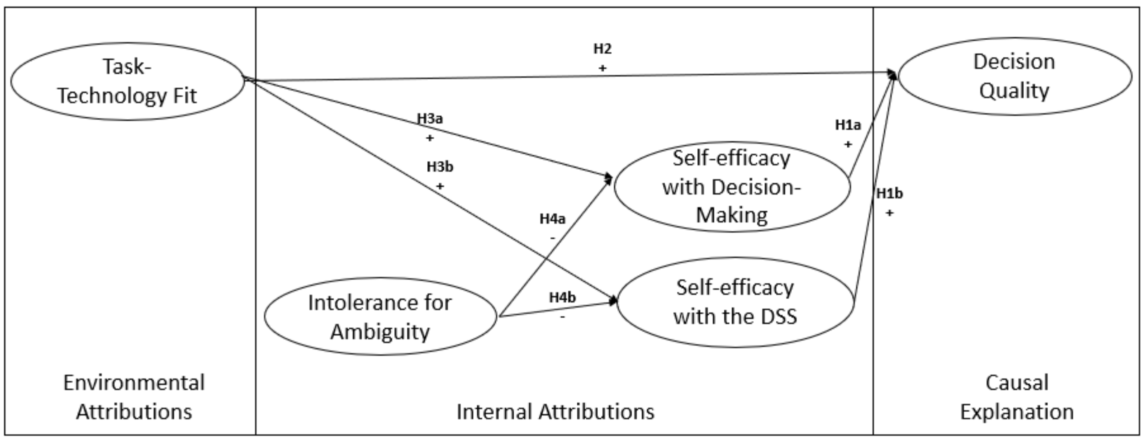

Figure 1. Theoretical model

Although there have been numerous and varied models of decision quality, very few have leveraged attribution theory as the model's foundation. Attribution theory describes how individuals perceive causality of outcomes (Fishman & Husman, 2017; Heider, 1944; Kelley & Michela, 1980; Weiner, 2010; Zhao, Detlor, & Connelly, 2016). This causality then drives actions and psychological states (Bandura, 1977). It works well in the business decision-making context because decision making is an individualized process; each individual approaches it differently (Adler, 1980; Korn, Rosenblau, Rodriguez Buritica, & Heekeren, 2016; Snead et al., 2015; Weiner, 1979).

Attribution theory begins with an outcome which an individual generally categorizes as a success or a failure (Heider, 1944; Kelley & Michela, 1980; Weiner, 1979). Next, causal attributions are considered by the individual. Causal attributions represent the information the individual needs to assign a causal factor and can be described as information, the individual's beliefs, or cognitive attributes of the individual assigning the causal factor to the outcome (Kelley & Michela, 1980). Focus in this stage is on how a causal assignment is made.

The research model uses a decision as the outcome to be considered and proposes that the individual's beliefs of self-efficacy both with decision-making (task) and with the DSS (technology), the individual's cognitive trait of tolerance for ambiguity, and how well the technology supports the decision task at hand (TTF).

This study argues that self-efficacy is a key attribute which impacts the individual's perception of decision quality. Consistent with past research, this study conceptualizes self-efficacy as two distinct constructs. Self-efficacy definitions often vary two aspects; specificity of the task and the technology (Gupta & Bostrom, 2019). The definition of self-efficacy with the decision task is the degree to which an individual believes in their ability to make a decision. The technology aspect is the self-efficacy with the decision support technology which is defined as the degree to which an individual believes in their ability to successfully use decision support technology to make decisions.

The definition of intolerance for ambiguity was adapted from Budner (1965) which was "the tendency to perceive ambiguous situations as a source of threat (p. 29). He then defined an ambiguous situation as a situation containing a lack of or conflicting informational cues (Budner, 1962). In the business decision context, ambiguous situations are often due to a unclear or puzzling input data (Coll et al., 1991; Hwang &

Lin, 1999; McIntyre & Ryans, 1983; O'Reilly, 1982; Speier, Valacich, & Vessey, 1999). In order to tighten the definition to fit the context of this study, the adaption was made.

TTF is defined as the degree to which an individual believes a technology fits the task at hand (Goodhue, 1995) and intolerance for ambiguity is defined as the degree to which an individual perceives puzzling information as a threat.

Self-Efficacy's Impact on Decision Quality

Gist and Mitchell (1992) found that the level of self-efficacy impacts how a person interprets feedback and how they interpret the outcome result. It does this by affecting the effort an individual applies toward their behavior and the persistence to persist past roadblocks (Bandura, 1977; Sherer et al., 1982). When a person has high self-efficacy, they tend to remain on-task, even in the face of challenges and failures (Lee & Bobko, 1994; Wood & Bandura, 1989). When challenges are encountered, a person with high self-efficacy will perceive the outcome as a function of effort and increase their effort level. A person with low self-efficacy will perceive it as a function of ability which causes doubt and diverts attention away from the problem at hand (Wood & Bandura, 1989).

This paper discriminates between two types of self-efficacy; with the decision task and with the decision support technology. This is important because past literature conceptualizes them together which may result in inconsistencies (Gupta & Bostrom, 2019). Conceptualizing them separately helps to provide better clarity into individual's beliefs and perceptions and ensures more accurate measurement. Self-efficacy with tasks is in regard to the actions needed to achieve the outcome. Decision-makers perform tasks based on their knowledge of the environment and their domain knowledge (Gupta & Bostrom, 2019). As a result, decision tasks rely more on psychological confidence rather than skill. Psychological confidence is the belief and motivation component of self-efficacy (Claggett & Goodwin, 2011).

Once a decision is reached, an individual with high self-efficacy with decision-making will not be distracted by doubt and will adjust the level of effort for future endeavors if needed, causing a more positive perception of the level of decision quality. Alternatively, an individual with low self-efficacy with decision-making will focus on their lack of or gaps in their abilities which will cause a more negative perception of the level of decision quality.

Therefore:

H1a. Self-efficacy with decision-making is positively related to decision quality.

Self-efficacy with the DSS is in regard to being able to use the decision support technology. This aspect of self-efficacy is more of a skill-based construct as opposed to psychological confidence (Claggett & Goodwin, 2011). Gupta and Bostrom (2019) coined specific complex self-efficacy (SC-SE) to represent specific software for complex tasks. They argued that SC-SE was determined by the level of skill the individual perceived they possessed. Gupta and Bostrom (2019) found that SC-SE had a significant impact on attitudes and argued the reason for this finding was because as individuals are learning the software for their specific task, they are also learning at a broader level to allow for future applications of the software.

Consistent with past literature, high self-efficacy with the DSS will be perceived as a function of effort and motivation. In the context of DSS, people who believe they are able to use the technology with great skill and/or believe she/he can improve that skill if greater effort is made, are more likely to expect positive outcomes in terms of high quality decisions.

Therefore:

H1b. Self-efficacy with the DSS is positively related to decision quality.

Task-Technology Fit's Impact on Decision Quality

Developing the belief of how well a technology fits the task at hand entails a cognitive process based on experiences (Goodhue, 1995; Parkes, 2013). When users evaluate systems, they consider the task from their perspective, their own experience level and needs, as well as factors relating to the system (Goodhue, 1995). As a result, users perceive TTF based on the extent to which the system meets their own needs.

Attributional factors have been shown to have the ability to directly affect the outcome without needing to assign attributions when the individual is in pursuit of a specific goal and feeling pertinent emotions (Weiner, 2010). This is consistent with Goodhue (1988), who argued that attitudes about TTF can impact performance directly. In these cases, the individual is focused on what happened as opposed to why it happened (Weiner, 2010).

A positive outlook regarding TTF will lead to positive psychological and behavioral consequences which increases the perceived outcome (Cheng, 2019; Tam & Oliveira, 2016) which, in the context of a decision task, means that an individual will likely perceive a higher decision quality. For example, if a task involves buying or selling commodities on the open market, then the decision-maker knows that real-time information is needed to perform their task well. If the individual perceives the tool as able to support real-time functions (high TTF), she or he will perceive high outcome decision quality. If a system that does not support real-time demands is used (low TTF), the decision-maker must complete the decision-making task without the most up-to-date data putting her or him at a disadvantage, resulting in a lower perception of decision quality.

Therefore:

H2. Decision makers will attribute their perception of TTF to their DQ, such that, greater the perception, greater the DQ.

Task-Technology Fit's Impact on Self-Efficacy

TTF as an attributional antecedent affects the attribution which is determined by the individual (Kelley & Michela, 1980). Attributions are affected by information, specifically of the context and attributions of prior outcomes. Picking up the example of the decision task relying on real-time data, if the system supports real-time then the TTF would be perceived as high. When outcomes are perceived as successful, the individual typically assigned internal factors such as ability, effort, and persistence, and failures are typically assigned to external factors such as luck and task difficulty (Graham, 1991; Lin, Huang, & Chiang, 2018; Snead et al., 2015; Weiner, 1985).

Therefore, if an individual perceives high TTF and a successful outcome, internal factors will be assigned, increasing their perception of self-efficacy with the decision task. If an individual perceives high TTF and a failed outcome, she or he will assign external factors which does not affect how the individual perceives their ability to make a future decision. However, when an individual perceives low TTF and the outcome as a success, she or he will experience doubt regarding having to make the decision with missing information, decreasing their perception of self-efficacy with the decision task. If an individual perceives low TTF and a failure, they will experience doubt regarding having to make the decision with missing information in addition to ineffectiveness (Pan, Pan, & Newman, 2007; Snead et al., 2015), decreasing their perception of self-efficacy with the decision task.

Therefore:

H3a. Task-technology fit is positively related to self-efficacy with decision-making.

Self-efficacy with the DSS is an individual's judgment of their ability to effectively use a DSS. As mentioned earlier, this construct is perceived as a skill construct. At a high level, consistent with Bandura's foundational research on self-efficacy (1977) and recent literature (Cheng, 2019; Tam & Oliveira, 2016), as individuals experience with technology increases, their beliefs of their level of skill increases. TTF has been shown to increase utilization (Goodhue & Thompson, 1995; Klopping & McKinney, 2004; Lin & Huang, 2008; Parkes, 2013; Tam & Oliveira, 2016; Wu, Chen, & Lin, 2007). As individuals feel that the technology is a good fit for their task (high TTF), they will continue or increase their use of that technology to support them in their decision tasks. The overall effect is that as TTF increases, so does the belief of the level of self-efficacy with the DSS.

Therefore:

H3b. Task-technology fit is positively related to self-efficacy with the DSS.

Intolerance for Ambiguity's Impact on Self-Efficacy

Intolerance for ambiguity is defined as the degree to which an individual perceives puzzling information as a threat. A person with a low intolerance for ambiguity is relatively comfortable in situations that lack structure or informational cues (Budner, 1962). This lack of structure well-describes today's business decision tasks (Abbasi, Sarker, & Chiang, 2016; Alalwan, Thomas, & Weistroffer, 2014). Every decision contains some level of ambiguity because it's not possible to have or to consider all relevant data and information to a business decision which increases the ambiguity of the decision context (Grisé & Gallupe, 1999; Quentin, Gilad, & Sheizaf, 2004).

Self-efficacy with a decision task relies on psychological confidence which deals with the perception of the ability to get help from the external environment (Claggett & Goodwin, 2011). Therefore, when an individual perceives their ability to get help to be high, their self-efficacy to make the decision is high. However, when an individual has a high intolerance for ambiguity , their tendency to look externally for information is low (Endres, Chowdhury, & Milner, 2009; Schaninger & Sciglimpaglia, 1981; Vandenbosch & Huff, 1997) resulting in a lower perceived ability to make the decision.

Therefore:

H4a. Intolerance for ambiguity is negatively related to self-efficacy with decision-making.

As mentioned, self-efficacy with the DSS is perceived as a skill-based construct. Also as mentioned, intolerance for ambiguity has been linked to an decreased information search and expanded information processing behavior (Endres et al., 2009; Schaninger & Sciglimpaglia, 1981; Vandenbosch & Huff, 1997). As a result, those with a low intolerance for ambiguity are not discouraged from obtaining more external support to help them better understand and use the decision support technology. This increased information will result in a higher perception of their skillset in using the technology.

Therefore:

H4b. Intolerance for ambiguity is negatively related to self-efficacy with the DSS.

Chapter Summary

The model follows attribution theory to explain the proposed causal attributes to perceived decision quality. Attributional theory allows for the focus to be on the point of view of the decision-maker. TTF serves to represent the decision support technology and the decision-makers view of whether that technology supports the needs of the task. This perception is proposed to have an affect directly on decision quality, as well as the decision-maker’s belief that she/he can make a decision and whether they can use the decision support technology. Intolerance for ambiguity and self-efficacy with decision-making and with the decision support technology are all internal to the decision-maker. The higher the intolerance for ambiguity, the less the decision-maker will believe that she/he can make a decision and be able to use the decision support technology successfully. Finally, the more a decision-maker believes she/he can make a decision or use the technology, the higher the resulting perceived decision quality.

CHAPTER 4: METHODOLOGY AND DATA ANALYSIS

This chapter presents the research design used to test the proposed research model and to answer the research question; what are the factors attributed by individual decision-makers that affect decision quality? It also analyzes the data collected.

This study includes a pilot and a primary study. A questionnaire was developed to test the model, which was modified after the pilot study. This method was chosen because, as the model is grounded in attribution theory, the measurement needed to capture the beliefs of the decision-maker. Surveys are a predetermined set of questions and/or statements designed to capture data from respondents regarding their individual characteristics and beliefs (Hair et al., 2016). The updated questionnaire was used to gather data for the primary study. This chapter describes the analysis approach used and presents the results for both the pilot and the primary study.

Pilot

The objective of the pilot is to measure and improve the instrument for the purpose of ensuring an accurate and validated instrument for the primary study. The pilot sample was college undergraduates who were completing an information systems course. This sample is appropriate because the students are responding to the survey using their own experiences.

Concern with using students as samples applies when the researchers ask students to answer as if they were a business manager or in some particular role that they do not have, or have ever had (Barr & Hitt, 1986). The students in the sample were college undergraduates who were completing an introductory information systems course. The course included a module regarding decision-making when supported by technology which was referred to in the instrument questions. Immediately after the decision-making exercise described below, the link to the web-based survey tool Qualtrics was sent to each student who volunteered to participate in the study. The decision task involved two decision-making tasks; the instructor led the class to complete the first to provide direction on how the tool worked then the students completed the second on their own. Details are in Appendices B and C. An alternate assignment to the survey was also provided; students could write a one-page paper on the value of using technology to support decisions. The students who completed either assignment received ten bonus points which totaled about 1% of their overall class grade.

Instrument

In order to ensure each construct was being measured consistent with the definitions and context, a detailed literature review was performed to obtain validated instruments. The definitions, contexts, and question wording were all evaluated to determine the level of fit to this study. For some constructs, described below, there were some existing items that fit our definition and context. In those cases, we retained these items and added new ones. For other constructs, where existing scales did not match our construct definitions, we created our own items. The following paragraphs detail each construct and highlights leading instruments to emphasize lack of fit. In some cases, specific instruments are referenced to highlight the logic used. This logic applies to all instruments which were considered.

Decision quality is defined in this study as the degree to which an individual believes that she or he has made the best choice. Numerous instruments were evaluated as described above (Aldag & Power, 1986; Amason, 1996; Carmeli & Schaubroeck, 2006; Meissner & Wulf, 2013; Seo, Lee, & Lee, 2013; Tan et al., 2010; Visinescu et al., 2017; Widing & Talarzyk, 1993; J. Xu, Benbasat, & Cenfetelli, 2014) a few are discussed here to demonstrate how each review was done and specific issues found which made their application in this study problematic.

Tan et al. (2010) defined a 3-item instrument which focused on choice, but the items are problematic, making it unsuitable for this study. First, one of the items states "I would have made the same choice if I would have done it again". This is the same statement as the first item in the survey which is "I have made the best choice" except that it requires an extra cognitive step to arrive at the same point. The second issue is that one of the items states "I believe I have selected the best model for both products". This wording is very study-specific and would most likely need to be modified anyway for future studies.

The decision quality items were informed by the instruments we reviewed and also by our own definition. The definition focuses on the degree of belief that a best choice is made. The items are provided in Appendix A and include "I believe I have selected the right option" and "I believe I made a poor decision". The answers will provide a scale of belief and include specific questions which are along that scale.

The definition for TTF is the degree to which an individual believes a technology fits the task at hand. Therefore, the instrument should measure the range of belief an individual has for that fit. Numerous instruments were evaluated as described above (Dishaw & Strong, 1999; Goodhue, 1998; Goodhue & Thompson, 1995; Jarupathirun & Zahedi, 2007; Klopping & McKinney, 2004; Lin & Huang, 2008; McGill & Klobas, 2009; Zhou, Lu, & Wang, 2010) and a few are discussed here to demonstrate how each review was done and specific issues found which made their application in this study problematic.

A very popular scale applied to measuring TTF is Goodhue (1995) and Goodhue (1998) which many other scales reference or are based upon. However, these scales seek to measure factors including quality, locatability, authorization, and ease of use. This study does not intend to measure these aspects because they are not within the scope of the study. Since this is a perceived scale, the items are drawn from the same source; perception. Thus, the items should reflect the same concept and, as such, should be highly correlated (Straub, Boudreau, & Gefen, 2004).

The items for TTF are provided in Appendix A, and include “I believe there is an excellent fit between the decision I've made and the decision support technology” and “I believe there is a mismatch between the decision I've made and the decision support technology”. Similar to decision quality, these items focus on the range of TTF.

The definition of intolerance for ambiguity is the to the degree to which an individual perceives puzzling information as a threat. Consistently, the instrument should measure the range of belief an individual has that unclear or puzzling information is threatening. Numerous instruments were evaluated as described above (Budner, 1962; Gu, Jiang, Oh, & Wang, 2018; Kirton, 1981; MacDonald, 1970; McLain, 1993; Norton,

1975) and a few are discussed here to demonstrate how each review was done and specific issues found which made their application in this study problematic.

Budner (1962) defined a popular instrument, however, it seeks to measure various factors which this study does not endeavor to quantify such as phenomological denial and operative submission. The items for intolerance for ambiguity are provided in Appendix A. They include “I am threatened by puzzling information” and “I am intimidated by perplexing information”.

The definition of self-efficacy with the DSS is the degree to which an individual believes in their ability to successfully use the DSS tools. Therefore, the instrument should focus on the range of beliefs an individual feels that they will be successful in using the DSS. Numerous instruments were evaluated as described above (Compeau & Higgins, 1995b; Hollenbeck & Brief, 1987; Marakas, Johnson, & Clay, 2007; Torkzadeh & Koufteros, 1994) and a few are discussed here to demonstrate how each review was done and specific issues found which made their application in this study problematic.

Many of the instruments endeavor to measure self-efficacy with specific tools including self-efficacy with Windows, spreadsheets, and the internet (Marakas et al., 2007) or specific skill levels including beginner and advanced (Marilyn Gist, 1989; Hill et al., 1987; Marakas et al., 1998; Torkzadeh & Koufteros, 1994; D. Xu, Heales, Huang, & Wang, 2014). The items on the Compeau and Higgins (1995b) instrument focus on the ability for others to help the respondent which more accurately would measure the abilities and efforts of those coworkers as opposed to the self-efficacy of the respondent. For example “I could complete the job using the software package if I could call someone for help if I got stuck” and “I could complete the job using the software package if someone else had helped me get started" (Compeau & Higgins, 1995b). In addition, the Compeau and Higgins (1995b) instrument was 16 items which was long and could have contributed to respondent fatigue (MacKenzie & Podsakoff, 2012) and specified dated technology.

The items for self-efficacy with the DSS are provided in Appendix A. They include "I believe I can adequately operate a decision support technology" and "I am unsure whether I can work with a decision support technology"

Self-efficacy with decision-making is defined as the degree to which an individual believes in their ability to make a decision. Therefore, the instrument should focus on the range of belief an individual feels that they will be able to make a decision. Numerous instruments were evaluated as described above (Chen, Gully, & Eden, 2001; Compeau & Higgins, 1995b; Marilyn Gist, 1989; Hill et al., 1987; Sherer et al., 1982; Taylor & Betz, 1983; Visinescu et al., 2017; D. Xu et al., 2014) and a few are discussed here to demonstrate how each review was done and specific issues found which made their application in this study problematic.

Many issues encountered here are similar to those found in self-efficacy with the DSS. In addition, many of the more general self-efficacy studies specifically mention aspects which this study is not focused on measuring. For example, "When I make plans, I am certain to make them work" and "If I can't do a job the first time, I keep trying until I can" (Sherer et al., 1982). Many items in self-efficacy instruments focus on outcomes or achievement which also do not fit this study. For example "I will be able to achieve most of the goals that I have set for myself" and "When facing difficult tasks, I am certain that I will accomplish them" (Chen et al., 2001).

The items for self-efficacy with decision-making are provided in Appendix A. They include “I am confident I can make a decision” and “I am unsure I can make a decision”.

Analysis

Partial Least Squares structural equation modeling (PLS-SEM) was used to evaluate the measurement model. Smart-PLS software package was used for the data analysis. PLS-SEM is a causal modeling approach with the objective of maximizing explained variance of the dependent constructs. PLS-SEM is typically leveraged when the research objective is prediction and theory development (Hair, Ringle, & Sarstedt, 2011). The purpose of this research is to understand how much variance in decision quality is explained by task-technology fit, intolerance for ambiguity, self-efficacy with decision-making, and self-efficacy with the decision support technology, therefore PLS-SEM is a good fit to evaluate the proposed model.

Primary Study

The purpose of the primary study, as shown in Appendix D, was to evaluate the research model. The sample was procured from Qualtrics. Qualtrics is a subscription software program which offers a platform to create and distribute surveys. It also offers a service which can identify and procure data from targeted populations.

The criteria (business decision-makers who use technology to support their decisions) and the instrument were provided to Qualtrics who then recruited the respondents to take the survey. Measures were taken to minimize the common methods bias through administration and design of the survey instrument as suggested by MacKenzie and Podsakoff (2012) including filtering the respondents so only those with the experience, ability, and knowledge provide data, simplification of questions to include clear, concise wording to reduce item ambiguity, and providing prompts to reduce the effort required which require retrospective recall. In addition, reverse items were included to decrease item repetitiveness and the questions were arranged so that no more than two questions on a single page were from the same construct (MacKenzie & Podsakoff, 2012). Harman's single factor test was run on and the total variance explained for a single factor was 23.90% which is well under the 50% upper limit (MacKenzie & Podsakoff, 2012; Tehseen, Ramayah, & Sajilan, 2017).

The model tested in this study is in Figure 1. The model was created consistent with attribution theory which states that environmental cause attributions affect internal causal attributions which then affects the perceived causality. The hypotheses which were tested were explained in previous chapters. A summary of these hypotheses are:

H1a. Self-efficacy with decision-making is positively related to decision quality.

H1b. Self-efficacy with the DSS is positively related to decision quality.

H2. Task-technology fit is positively related to decision quality.

H3a. Task-technology fit is positively related to self-efficacy with decision-making.

H3b. Task-technology fit is positively related to self-efficacy with the DSS.

H4a. Intolerance for ambiguity is negatively related to self-efficacy with decision-making.

H4b. Intolerance for ambiguity is negatively related to self-efficacy with the DSS.

Pilot Analysis

The pilot test, as detailed in Appendices B and C, was performed to validate the measurement instrument discussed in the previous chapter. The study used a sample of university undergraduates who were enrolled in a computer science course in a university in the southern United States. The study was performed at the end of the semester, so the students had sufficient understanding of Excel which was the tool used on the in-class activity. The pilot survey (Appendix B) was distributed via a link to a survey in the Qualtrics platform after a class activity regarding technology-supported decision-making. The pilot survey instructions and questions were modified to reflect the class setting.

The instructions were tailored to the specific in-class activity described later in this section. For example, the decision support technology used was MS Excel so the instruction "As a reminder, the decision support tool we used during the in-class activity was Excel" was inserted. This was done to ensure understanding and improve accuracy. The instrument was measured via a 1-7 Likert-type scale, where 1 is strongly disagree and 7 is strongly agree. Appendix B contains the full survey.

Of the 104 students enrolled in the class, 87 submitted the survey (83.7% response rate). Three records were removed because they were incomplete, leaving 84 records to be considered in the measurement model. Of the 84 respondents, 45 were male (53.6%) and 39 were female (46.4%). The ages ranged from 18 to 24 years of age, with only one respondent in the 25 – 34 years old range. A total of 82.1% of the students stated that they did not have any experience using technology to make decisions. This was expected which is why the in-class activity of making decisions using Excel as the decision support technology was completed prior to the study. A total of 10.7% had .5 – 2 years of experience making decisions supported by technology and 7.1% had more than 2 years. Please see Table 3 for a summary of these demographics.

Table 3

Pilot Participant Demographic Information

	Totals	Percent
Gender		
Male	45	54%
Female	39	46%
Age (Years)		
18 – 24	83	99%
25 – 34	1	1%
Experience (Years)		
None	69	82%
.5 – 2	9	11%
> 2	6	7%

Validity and Reliability

Steps were taken to test the measurement model, specifically internal consistency, convergent validity, and discriminant validity. The constructs measured were decision quality (DQ), self-efficacy with decision-making (SEDM), self-efficacy with the decision support technology (SEDSS), intolerance for ambiguity (IAMBIG), and task-technology fit (TTF). A confirmatory factor analysis (CFA) was performed to analyze the results.

Convergent validity was considered first by evaluating the outer loadings and AVE. As shown in Table 4, most of the proposed items showed acceptable loading scores, which is 0.7 or greater (Hair, Black, Babin, & Anderson, 2010). Average variance extracted (AVE) indicates how much of the variance is explained by the construct as opposed to explained by error. As shown in Table 6, each AVE is above the .5 threshold.

Table 4

Pilot CFA Outer Loadings

Construct	Item	Outer Loading
DQ	DQ1	0.664
	DQ2	0.797
	DQ3	0.881
	DQ4	0.798
	DQ5-R	0.820
	DQ6	0.404
IAMBIG	IAMBIG1	0.759
	IAMBIG2	0.732
	IAMBIG3	0.905
	IAMBIG4	0.728
	IAMBIG5-R	0.223
	IAMBIG6-R	0.465
SEDM	SEDM1	0.528
	SEDM2	0.828
	SEDM3	0.843
	SEDM4-R	0.700
	SEDM5-R	0.863
	SEDM6-R	0.814
SEDSS	SEDSS1	0.763
	SEDSS2	0.805
	SEDSS3	0.811
	SEDSS4-R	0.770
	SEDSS5-R	0.762
TTF	TTF1	0.850
	TTF2	0.896
	TTF3-R	0.764
	TTF4-R	0.819
	TTF5-R	0.771

Items were removed in a systematic way based on their overall loading onto the construct as well as their level of cross-loadings onto other constructs. Each item was analyzed, and a single problematic item was removed. The path model was then re-run and re-analyzed and more items were removed until the model contained good measurement items. The following items were removed to improve Cronbach's Alpha and resolve cross-loading issues; DQ1, DQ5R, DQ6, IAMBIG4, IAMBIG5R, IAMBIG6R, SEDM1, SEDM4R, SEDM6R, SEDSS1, SEDSS5R, and TTF5R. The overall model scores improved with the removal of these items. The new items loadings for the new model is in Table 5. Using the remaining items, the subsequent tests were performed.

Table 5

Pilot Final Model CFA Outer Loadings

Construct	Item	Outer Loading	P Values
DQ	DQ2	0.843	0.00
	DQ3	0.919	0.00
	DQ4	0.857	0.00
IAMBIG	IAMBIG1	0.770	0.00
	IAMBIG2	0.750	0.00
	IAMBIG3	0.914	0.00
SEDM	SEDM2	0.875	0.00
	SEDM3	0.908	0.00
	SEDM5-R	0.864	0.00
SEDSS	SEDSS2	0.841	0.00
	SEDSS3	0.862	0.00
	SEDSS4-R	0.777	0.00
TTF	TTF1	0.852	0.00
	TTF2	0.903	0.00
	TTF3-R	0.804	0.00
	TTF4-R	0.832	0.00

Internal consistency was considered next. Chronbach's Alpha (α) is often used to estimate reliability based on the intercorrelations of observed indicator variables. However, α assumes all indicators are equally reliable, but PLS-SEM prioritizes indicators according to individual reliabilities (Hair, Hult, Ringle, & Sarstedt, 2017). The effect is that α often under-estimates internal consistency reliability so can be used as a conservative measure. Composite reliability is more reliable and consistent with the PLS-SEM methodology, thus is the preferred value to use when establishing internal consistency (Hair et al., 2017). As shown in Table 6, both measures indicate good internal consistency.

A test which is commonly run in PLS-SEM tests to help establish discriminant validity is the Fornell-Larcker method. The Fornell-Larcker criterion compares the square root of the AVE values with the latent variable correlations. The square root of each construct's AVE should be greater than its highest correlation with any other construct. The logic of this method is based on "the idea that a construct shares more variance with its associated indicators than with any other construct" (Hair et al., 2017, p. 116). As seen in Table 6, this requirement is met. This outcome implies discriminant validity.

Table 6

Pilot Reliability and Discriminant Validity

	α	Composite Reliability	AVE	DQ	IAMBIG	SEDM	SEDSS	TTF
DQ	0.845	0.906	0.763	0.874				
IAMBIG	0.743	0.855	0.664	-0.399	0.815			
SEDM	0.858	0.914	0.779	0.588	-0.488	0.883		
SEDSS	0.769	0.867	0.685	0.642	-0.407	0.508	0.828	
TTF	0.870	0.911	0.720	0.747	-0.236	0.271	0.706	0.848

In addition to evaluating the outer loadings and the Fornell-Larker test, PLS-SEM often uses the heterotrait-monotrait ratio (HTMT) to ensure discriminant validity. An HTMT value above .9 indicates a lack of discriminant validity. As shown in Table 7, all items are below this threshold. Given this outcome in addition to positive results from the other two discriminant tests, it is determined that the model has sufficient discriminant validity.

Table 7

Summary of the HTMT Test

	DQ	IAMBIG	SEDM	SEDSS
IAMBIG	0.494			
SEDM	0.688	0.600		
SEDSS	0.788	0.536	0.625	
TTF	0.543	0.297	0.312	0.858

Due to the results discussed in this section, it was determined that the instrument which was developed for this study was adequate to measure each construct in the proposed model. This instrument was then used in the primary study. The purpose of the primary study was to test the structural model and evaluate the proposed hypotheses.

Primary Study Data Analysis

The objective of the primary study was to test the entire research model which includes the measurement model and the structural model. The sample included business decision-makers who use technology to support their decisions. Qualtrics was contracted to identify the participants, gather their responses, and respond to the researchers with any concerns.

The Qualtrics survey contained prompts and filters to ensure that only business decision-makers who used technology to make their decisions were included. An upper limit and a lower limit were applied to all survey responses. There were 42 question and instruction statements on the survey, and it was determined that a minimum of three seconds per statement was needed to properly understand and respond to it. As a result, any completed survey which took less than two minutes was removed. The 20-minute upper threshold was based on the professional experience of the Qualtrics project manager and his awareness of survey responses (Johnston, Warkentin, Dennis, & Siponen, 2019).

The data was gathered in two rounds. Once the first-round data was collected, a question emerged regarding whether instruments used and validated in prior research would perform better than the items defined for this study. To address this question, three items were added to SEDM which were drawn from Chen et al., (2001); “When facing difficult decisions, I am certain that I will be able to make them”, “I am confident that I can perform effectively on many different decision tasks”, and “Even when things are tough, I can perform decision-making quite well”. Another question which arose was whether the IAMBIG6R item “I perceive certainty when information is clear” was written in a way which was consistently understood by the respondents. In an effort to make it more clear, the item “I believe that clear information is desirable” was added.

In order to ensure the data in the two groups were not statistically different, independent t-tests were performed on age, education, and experience. The significance for the equal variances assumed were above the .05 threshold which means that based on these variables, the two groups were not statistically different.

The added items did not load well so were dropped to arrive to the final model. The filter criteria were the same for each round. Since each round was taken randomly from the same population, the results of the two rounds were combined to perform the primary study analysis.

The total number of records not accepted by Qualtrics prior to their being made available was not reported. There were 633 records were provided in total (round one and round two), of which 413 were usable (65%) due to 220 being incomplete or inaccurate. At a deeper level of detail, the first round resulted in 230 records, of which 129 were usable which represents about 56% acceptance rate. The second round resulted in 403 records, of which 284 were usable which is a 70% acceptance rate. There were issues of the respondents choosing the same value in a majority of the responses (straightlining); those records which contained straightlining were rejected. Straightlining is an issue in two ways. First, in many cases, straightlining was applied to the entire set of items. Second, there was straightlining applied within the constructs, even when reverse-coded items were used (Hair et al., 2017). In order to determine which records contained straight-lining, the mode of the responses to the Likert questions was calculated in each round. All records with a mode of any particular numbered response over 80% were eliminated. This resulted in removing 129 records from round one and 213 in the first round. In the second round, 71 were also removed for non-sensical answers for a qualitative control question which was inserted for this round (the qualitative question did not exist in the second round).

About 49% of the respondents received a 4-year college degree or higher, 14% had an associate degree, 22% had received some college credit and 15% had a high school degree. About 19% had at least two years of experience, 27% had over two and under five years of experience, 18% had over five years and under 7 years of experience, and 37% had over seven years of experience. There were no respondents under 18 and five over 65 years of age. About 14% were between 18 and 24, 30% were older than 24 and younger than 34, 28% were older than 34 and younger than 44, 18% were older than 44 and younger than 54, and 10% were older than 54 and younger than 65. 30% identified as male, 68% identified as female, and 3 respondents opted out of answering this question. The summary of these demographics are presented in Table 8. Changes from the Pilot included the removal of the items listed in the previous section. All other items from the Pilot were initially included.

Table 8

Primary Study Participant Demographic Information

	Round 1	Round 2	Combined
Gender			
Male	25	100	125
Female	103	179	282
Other	1	5	6
Age (Years)			
18 – 24	15	44	59
25 – 34	50	72	122
35 – 44	30	84	114
45 – 54	19	54	73
55 – 65	14	26	40
65+	1	4	5
Experience (Years)			
< 1	0	15	15
1 – 2	27	33	60
2.5 – 5	40	70	110
5.5 – 7	21	55	76
7+	41	111	152
Education			
High School	29	33	63
Some College	29	63	92
Associate Degree	18	38	56
Bachelor's Degree	36	101	137
Master's Degree	14	41	55
Doctorate Degree	3	8	11

Statistical Controls

This study contained several control factors that could influence the causal attribution process. Participants gender, age, education level, and years of experience were used as statistical controls. None of the control variables were significant so they were not included in the final model. Table 9 shows the statistical significance of those variables.

Table 9

Control Variable Statistics

Control Variable	Factor Loading	T Statistic	P Value
Gender	.009	.188	.425
Age	-0.042	.853	.197
Education Level	.040	.960	.169
Years of Experience	0.32	.586	.279

Validity and Reliability

Similar to the pilot, steps were taken to test internal consistency, convergent validity, and discriminant validity. The constructs measured were decision quality (DQ), self-efficacy with decision-making (SEDM), self-efficacy with the decision support technology (SEDSS), intolerance for ambiguity (IAMBIG), and task-technology fit (TTF). CFA was performed using Smart-PLS, version 3.

Convergent validity was considered first by evaluating the outer loadings and AVE. As shown in Table 10, most of the proposed items showed acceptable loading scores, which is 0.7 or greater (Hair, Black, Babin, & Anderson, 2010). Average variance extracted (AVE) indicates how much of the variance is explained by the construct as opposed to explained by error. As shown in Table 11, each AVE is above the .5 threshold. The primary study's cross loadings are provided in Appendix E.

Table 10

Primary Study CFA Outer Loadings

Construct	Item	Outer Loading	P Values
DQ	DQ2	0.841	0.000
	DQ4	0.846	0.000
	DQ5-R	0.720	0.000
IAMBIG	IAMBIG1	0.880	0.000
	IAMBIG	0.670	0.000
	IAMBIG3	0.841	0.000
SEDM	SEDM2	0.829	0.000
	SEDM3	0.670	0.000
	SEDM5-R	0.826	0.000
SEDSS	SEDSS2	0.870	0.000
	SEDSS3	0.462	0.000
	SEDSS4-R	0.807	0.000
TTF	TTF1	0.807	0.000
	TTF2	0.808	0.000
	TTF3-R	0.282	0.000
	TTF4-R	0.526	0.000

In order to measure the construct consistently with the theoretical meaning, the definition was consulted. The definition of TTF is the degree to which an individual believes a technology fits the task at hand. Based on this, TTF1 and TTF2 fit this definition because they articulate “a good match” and “an excellent fit”. The other two items articulate “a mismatch” and “not well-suited”. Therefore, to ensure consistency with the definition, the negatively worded items were dropped. Although a two-item scale isn’t preferable, literature has even contained constructs measured by a single item (Hair et al., 2010) and the “two indicator rule” is accepted in the literature (Kenny, 2011). Also, the objective of PLS is to determine how much weight to allocate to each item to maximize the amount of variance of the dependent variable which is explained by the independent variables (Hair et al, 2017). The issue with a two-item scale for a construct is within covariance-based structural equation modeling which results in identification issues.

The literature supports that it is sufficient to measure a construct with two items, therefore this has been accepted as a limitation and the results as accurate. The remaining items' loadings are in Table 11. The subsequent tests were run with remaining items.

Table 11

Primary Study Final Model CFA Outer Loadings

Construct	Item	Outer Loading	P Values
DQ	DQ2	0.840	0.000
	DQ4	0.847	0.000
	DQ5-R	0.719	0.000
IAMBIG	IAMBIG1	0.882	0.000
	IAMBIG2	0.668	0.000
	IAMBIG3	0.841	0.000
SEDM	SEDM2	0.852	0.000
	SEDM3	0.832	0.000
	SEDM5-R	0.663	0.000
SEDSS	SEDSS2	0.831	0.000
	SEDSS3	0.873	0.000
	SEDSS4-R	0.443	0.000
TTF	TTF1	0.839	0.000
	TTF2	0.853	0.000

There were three loadings which are under the threshold; IAMBIG2, SEDM5-R, and SEDSS4-R. They were not removed so that construct validity could be retained. IAMBIG2 states "I am indecisive when facing unclear information". This item is needed to retain construct validity because the measurement of this construct measures the degree of belief. The other two items focus on the degree the individual feels threatened by information and the degree the individual feels intimidated. The study's focus is on decision quality which is why this item is needed. Similarly, SEDM5-R states "I am unsure I can make a decision"; the other two items ask the degree to which the individual feels highly capable and confident. Lastly, SEDSS4-R asks “I am unsure whether I can work with a decision support technology”. The other two items focus on the degree to which the individual feels adequate and confident to work with the technology. It is not uncommon to obtain some low loadings when working with newly developed scales (Hulland, 1999).

Internal consistency was considered next. Cronbach’s Alpha (CA) is often used to estimate reliability based on the intercorrelations of observed indicator variables. As shown in Table 10, three of the constructs are below the acceptable CA threshold (SEDM, SEDSS, and TTF). However, as discussed earlier, the calculation for CA isn’t consistent with the way PLS-SEM is calculated and often under-estimates the internal consistency reliability. The measure which is relied upon more for PLS-SEM is the composite reliability score. All values are between the established scores of 0.7 and 0.9 for this measure.

Due to the results discussed in this section, it was determined that the measurement model is sufficient. The next step is to evaluate the structural model to determine its predictive capabilities.

The Fornell-Larcker method was leveraged to continue the discriminant validity test. Each AVE (located in the diagonals) is greater than the internal factor correlations underneath it which implies discriminant validity. All results are sufficient therefore composite reliability is established. These results are in Table 12.

Table 12

Primary Study Reliability and Discriminant Validity

	α	Composite Reliability	AVE	DQ	IAMBIG	SEDM	SEDSS	TTF
DQ	0.728	0.845	0.647	0.804				
IAMBIG	0.729	0.842	0.643	-0.182	0.802			
SEDM	0.690	0.828	0.619	0.576	-0.375	0.787		
SEDSS	0.584	0.773	0.550	0.625	-0.294	0.582	0.741	
TTF	0.603	0.834	0.716	0.687	-0.264	0.479	0.576	0.846

The last test to establish discriminant validity is the HTMT test. Three values are slightly above the .9 threshold. However, the combination of the three tests indicate that the model has sufficient discriminant validity. The HTMT results are in Table 13.

Table 13

Summary of the Primary Study HTMT Test

	DQ	IAMBIG	SEDM	SEDSS
IAMBIG	0.227			
SEDM	0.769	0.524		
SEDSS	0.857	0.589	0.904	
TTF	1.021	0.395	0.732	0.902

Structural Model Evaluation

In order to establish the structural model, four tests are evaluated; a collinearity assessment, an evaluation of the path coefficients, and evaluations of the model's explanatory power (R^2 adjusted) and effect size (f^2).

The collinearity assessment is evaluated by considering the inner variance inflation factor (VIF). All VIF values were less than the threshold of 5. The path coefficients are shown in Table 14.

Table 14

Primary Study Path Coefficients

DV	IV	Path Coefficient	T-Statistic	P Value
DQ	SEDM	0.225	3.975	0.000
DQ	SEDSS	0.239	4.001	0.000
DQ	TTF	0.442	8.680	0.000
SEDM	IAMBIG	-0.267	4.640	0.000
SEDM	TTF	0.409	7.492	0.000
SEDSS	IAMBIG	0-.153	2.604	.005
SEDSS	TTF	.535	10.475	0.000

The adjusted coefficient of determination (R^2_{adj}) is used to estimate the amount of variance explained by the model. R^2_{adj} for DQ, SEDM, and SEDSS are 58.0%, 29.3%, and 35.0% respectively. The effect size (f^2) allows the analysis of the relevance of constructs in explaining endogenous constructs; in other words, how much a predictor construct contributes to the R^2 of the target construct. Results are determined as small (.02), medium (.15), or large (.35) effect sizes (Cohen, 1988). Table 15 displays the effect sizes for each relationship in the model.

Table 15

Primary Study Effect Sizes

Construct	Item	f square	Effect Size
DQ	SEDM	0.077	Small
DQ	SEDSS	0.075	Small
DQ	TTF	0.298	Medium
SEDM	IAMBIG	0.094	Small
SEDM	TTF	0.221	Medium
SEDSS	IAMBIG	0.034	Small
SEDSS	TTF	0.412	Large

The model's standardized root mean square residual (SRMR) is 0.105 which is above the .08 upper limit. Although this indicates potential issues with the model, the

SRMR isn't the recommended test for PLS-SEM analysis (Henseler & Sarstedt, 2013). The primary reason is that the goodness-of-fit statistics are not transferrable to PLS-SEM is the differences in the objectives of PLS-SEM and covariance-based SEM (CB-SEM); PLS-SEM's objective is to maximize the explained variance as opposed to minimizing the differences between covariance matrices (Joseph Hair et al., 2017). Some researchers have even gone so far as to state that using the traditional goodness-of-fit measures with PLS-SEM adds little to no value and recommend that they not be considered when using PLS-SEM (Joseph Hair et al., 2017; Rigdon, 2012). The path coefficients and statistical significance of the model can be found in Figure 2.

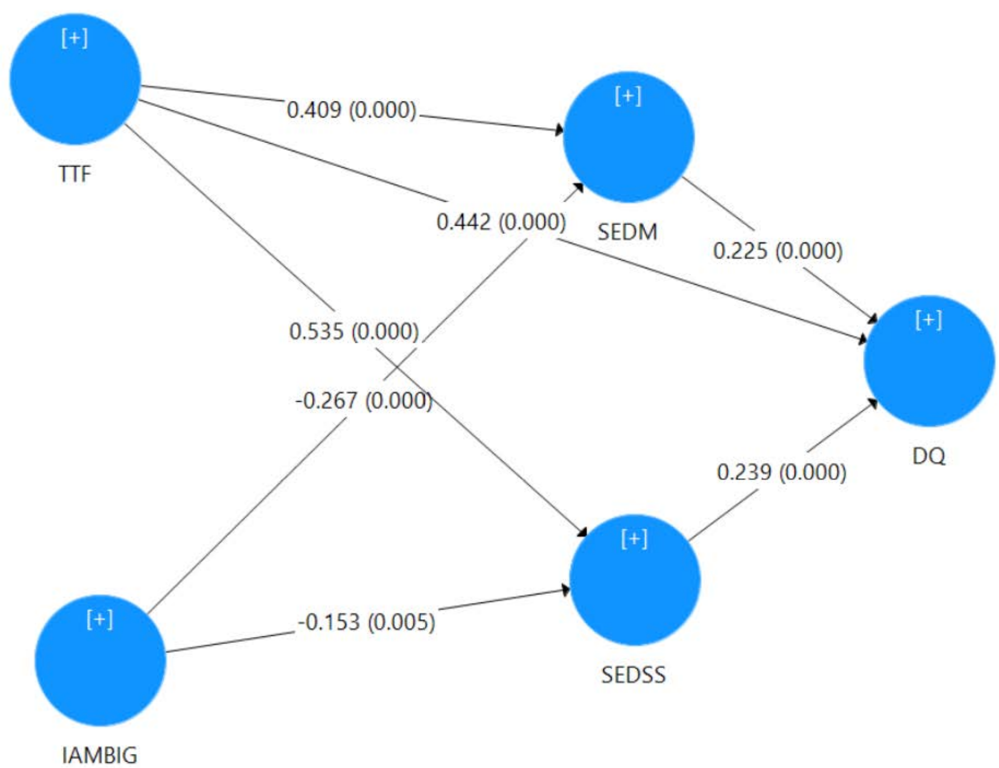

Figure 2: Primary study path coefficients and significance

The analysis of the results show that all proposed hypotheses are supported. Table 16 summarizes all of the proposed hypotheses and the conclusion as described in this section.

Table 16

Primary Study Hypotheses and Results

Hypothesis	Analysis Results
H1a. Self-efficacy with decision-making is positively related to decision quality.	Supported
H1b. Self-efficacy with the decision support technology is positively related to decision quality.	Supported
H2. Task-technology fit is positively related to decision quality.	Supported
H3a. Task-technology fit is positively related to self-efficacy with decision-making.	Supported
H3b. Task-technology fit is positively related to self-efficacy with the decision support technology.	Supported
H4a. Intolerance for ambiguity is negatively related to self-efficacy with decision-making.	Supported
H4b. Intolerance for ambiguity is negatively related to self-efficacy with the DSS.	Supported

CHAPTER 5 – DISCUSSION

This chapter discusses the interpretation of the results, limitations and contributions of the study, and future research recommendations. The chapter begins with a discussion of the results and hypotheses to gain a deeper understanding of the outcomes.

Interpretation of Results

Attribution theory was used to anchor the focus on decision-makers' perceptions of causality. This research asked individual decision-makers to determine what led them to their decision, thus examining how they reached the resulting decision quality (high or low). The model included an environmental attribute of task-technology fit, internal causal attributions of intolerance for ambiguity, self-efficacy with decision-making, and self-efficacy with decision support technology, and, finally, the dependent variable of decision quality.

Primary Study Findings

The primary study used Qualtrics which is a crowdsourcing service provider. Thirty-five percent of the records were rejected (35%), most due to straightlining. The reverse-coded items were key in this evaluation because they facilitated the determination of whether the respondents were reading the questions adequately. This is in stark contrast to the three pilot records which were removed (3%). This may indicate that face-to-face or a more targeted sample approach yields more accurate data.

Discriminant validity was established because of the results of the combination of three tests; analysis of the outer loadings, the Fornell-Larcker method, and the HTMT test. However, the HTMT test reported three issues. SEDSS and SEDM, SEDSS and TTF, and TTF and DQ were above the .9 threshold (.904, .902, and 1.021 respectively).

All of these relationships in the pilot were below the .9 upper limit and TTF. It's possible that the higher discriminant validity values from the pilot study were due to performing the decision-making module and activity directly prior to taking the survey. The lessons from the class module may have helped the students discern the questions more clearly.

Findings from the analysis of the structural model indicate that all hypothesized relationships were supported. However, the interesting aspects are at a more detailed level. For example, out of the three proposed independent variables affecting the dependent variable of DQ, TTF had a much larger coefficient in the relationship with decision quality (.442) than self-efficacy with decision-making (.225) or self-efficacy with the DSS (.239).

This finding could be interpreted that as long as the technology is perceived as a fit, that self-efficacy plays a smaller role when the decision-makers determine the level of decision quality. This phenomenon can be found in extant literature; that individuals feel that the decision outcome is enhanced when supported by a technology because they perceive that the technology allows them to fully explore the problem in depth and consider many more inputs than if they did not have the technology (Tan et al., 2010).

Also, it has been found that technology allows for a decrease in cognitive effort which increases satisfaction with the decision outcome (Kamis, Koufaris, & Stern, 2008). Another potential explanation could be that analysis needs to be done on the instrument. There were some indications of issues which may have contributed to this finding, specifically with discriminant validity.

In order to gain more insight, an ad hoc test was run on the pilot study to allow for comparison of structural and model paths to the primary study. Initially, these tests were not done since the purpose of the pilot was to test the measurement model, not the structural model. The p-value for the path coefficient for the relationship between TTF and DQ was above .05 (.168), thus it is not supported. SEDM had the highest effect on DQ (medium to large effect of .197) followed by SEDSS (small to medium effect of .118).

This difference could be a result of the sample frames. Students had little experience with decision support technology as the class they were in included an introduction to Excel which was the decision-tool used in the module. As a result, they could feel anxiety or be unsure of whether the technology is a good fit for the task. Another potential explanation could be that the students perceived the decision to be of higher complexity since it was their first time making it, as opposed to business decision-makers who may know more about the context of the decision which could decrease the perception of complexity. As a result, future research could include a focus on the decision complexity as perceived by the decision-maker as well as the experience level and frequency of that particular decision. The difference could point to a potential issue with generalizability of the model, however there is not strong evidence to support this conclusion. There is support in the literature that shows the path strength may vary among populations, but the model is still supported in those populations. King and He (2006) discusses this in terms of students, professionals, and general users and Schepers and Wetzels (2007) discusses it in terms of students and non-students as well as western versus eastern subjects.

This study focused on decision quality from the point of view of the decision-maker. The results of the study show that, in a business context, when decision-makers are supported by technology, they consider aspects both inside themselves and in the environment. The environmental attribute of TTF is significant in informing the decision-maker's self-efficacy with decision-making in general and self-efficacy with the DSS as well as directly on decision quality. This speaks to the importance of having the right tool for the right task. The study has also shown support that the decision-maker's intolerance for ambiguity is important when forming that decision-maker's self-efficacy with decision-making and self-efficacy with the DSS. When there is a lack of clarity or when there are conflicting information cues, both of these self-efficacy constructs are negatively impacted. Once the decision-maker's self-efficacy with decision-making and self-efficacy with the DSS has been formed, they have a significant and positive impact on decision quality.

A post-hoc test which was completed was to better understand the different behavior of the positively-worded and negatively-worded TTF items. To better understand, TTF was divided into two constructs in the PLS-SEM model; the first identified as TTFPos, which contained the positively worded TTF1 and TTF2 items, and TTFNeg, which contained the negatively worded TTF3-R and TTF4-R items. TTFNeg did not have significant relationships with any of the proposed constructs (SEDM, SEDSS, DQ). This implies that the negatively worded items and the positively worded items are not measuring the same theoretical construct. Past research supports that this issue can occur with negatively-worded items Hughes, 2009; Weems & Onwuegbuzie, 2001).

In conclusion, the findings from the primary study supported the proposed hypotheses. Task-technology fit in combination with self-efficacy for the task and the technology have a direct effect on decision quality. In addition, the personality trait of intolerance for ambiguity has significant impact on self-efficacy with the decision-task and with the decision support technology. Specifically, as TTF increases by one unit, decision quality increases by .442, as self-efficacy with decision-making increases by one unit, decision quality increases by .239, and as self-efficacy with the DSS increases by one unit, decision quality increases by .225.

Limitations

Limitations are a part of every research study and this study is not an exception. Limitations with the primary study include the use of Qualtrics to obtain the survey respondents. Obtaining sample data from online services such as Qualtrics and Mechanical Turk (MTurk) are becoming more popular in academic journals (Chang & Vowles, 2013; Kees, Berry, Burton, & Sheehan, 2017). Some of the weaknesses include unknown truthfulness and populations (Chang & Vowles, 2013; Hillygus, Jackson, & Young, 2014; Smith, Roster, Golden, & Albaum, 2016).

However, there is support stating that crowdsourced surveys are of equal or greater quality than paper surveys and/or student surveys. Chang and Vowles (2013) performed a study to compare the results of a crowdsourced survey versus a paper survey, and the crowdsourced survey out-performed the paper version. Roulin (2015) compared nine independent samples; two from MTurk with U.S. participants, four from Qualtrics crowdsourced panels, and three samples with business students. He found that the crowdsourced samples more accurately represent the working population than business students which may be beneficial depending on the study. He also found that the online populations had higher accuracy than the business student samples. Kees et al. (2017) compared five samples. They found that MTurk data outperformed panel data procured from two separate professional marketing research companies across various measures of data quality. The MTurk data were also compared to two different student samples, and results show the data were at least comparable in quality.

To control for this limitation, Qualtrics was provided with filters including that the respondent had to be a decision-maker within their company, that the minimum survey completion time was 3.5 minutes, and the maximum survey time was 20 minutes. Responses were also rejected which did not fit the target sample or that had issues such as straightlining. We also accept this limitation as the literature supports the use of crowdsourced survey services.

Related to the Qualtrics data, two populations were combined into a single data set to test the model. Any time two datasets are combined, there may be multigroup issues which may impact the results. The t-tests determined that the two samples weren’t significantly different, but there may be undiscovered issues.

Another limitation is that there wasn't an attempt to center on a specific type of decision or a specific set of decision support technologies. Many studies include experiments in the research design to control for these aspects, however, realism can be lost. In an attempt to anchor the responses, there was a prompt in the survey instructions to think of a specific time they made a decision which was supported by a decision support technology.

There is a limitation regarding the HTMT test which was used to establish discriminant validity in the primary study. Specifically, there were three problematic pairs; DQ and TTF (1.021), SEDM and SEDSS (.904), and SEDSS and TTF (.902). Although it can be argued that .902 and .904 are very close to .9, especially if rounded to two decimal places, the 1.021 is a definite problem. Since the Fornell-Larker test did not report issues, these values were accepted for this study. However, it is a limitation and an area for future research to understand these values and why one discriminant validity test passed and another didn't.

In conclusion, the limitations were identified and mitigated, resulting in an acceptable level of risk. These limitations open doors for future research which will be discussed later in this chapter.

Contributions

This research focuses on how individual decision-makers form perceptions of decision quality and of the resulting psychological and behavioral consequences. Theoretical contributions include combining a priori and observation-based methods to better capture the decision-maker's point of view and understanding of psychological processes. This study also combines two theories; task-technology fit and attribution theory to explain these relationships at a deeper level.

The practical contributions include informing managers who lead individual decision-makers how decision-makers approach decision tasks by providing empirical support for the idea that taking action to improve perceptions of TTF, tolerance for ambiguity, and self-efficacy can positively improve decision quality. Managers may find that implementing measures to improve awareness of DSS functionalities and how those functions support decision tasks as well as measures to improve self-efficacy using the three lenses offered here. Managers may also find that specifically evaluating aspects of an individual's tolerance for ambiguity and self-efficacy when hiring may result in employees who better fit into a decision-maker role. Lastly, the results of this research could provide organizations which design and create decision support systems with insight into how decision makers evaluate the resulting decisions. This could be invaluable to ensure that the needs of those individuals are met by the system, thus increasing TTF.

Future Research

During the result evaluation, it was found that the level of understanding of the decision task itself or of the decision task environment may impact self-efficacy and how the attributions of decision quality are determined. The context of a task is very difficult to define and measure , as it is highly nebulous and could refer to many aspects such as the cause-and-effect relationships of input and output variables, aspects of the decision tool, the input and output processes, and actions of the decision-maker. The question regarding the decision context is wide-ranging and includes the understanding of the goals, tasks, issues, and opportunities that define business needs surrounding the decision task (Hevner, March, Park, & Ram, 2004). Therefore, a potential future research direction could be to identify, define, conceptualize, and measure decision context to understand its impact on decision-makers.

An items which was identified during the analysis was that there was an inconsistency between the HTMT test and the Fornell-Larker test. It is not clear what caused this inconsistency and the results could shed light on how to better interpret and/or improve upon this study.

Another area of future research is to better understand if and how using online services to obtain data compares to more traditional methods. Currently, the research is not clear on whether face-to-face survey methods yield more or less accurate results than by using services such as Qualtrics. There is support stating that online surveys are of equal or greater quality than paper surveys and/or student surveys (Chang & Vowles, 2013; Kees et al., 2017; Roulin, 2015). There is also support stating that online surveys are of less quality than paper surveys and/or student surveys (Hillygus et al., 2014; Kaminska, Mccutcheon, & Billiet, 2010; Smith et al., 2016). Given that these service providers are relatively new, more research is warranted.

An articulated limitation is that some research finds respondents obtained via online platforms to be of less quality than if the researchers obtain the respondents. Therefore, an area of future research is to further evaluate the quality of results from these sources as compared to face-to-face surveys or surveys of specifically targeted companies, roles, or individuals.

Another area of future research is to use the findings from this research to test the actual impact on individuals. Interventions can be identified and executed in order to compare the before and after decision-maker attributions. This can help provide insight into how to operationalize these results.

Conclusion

This research presented a theoretically grounded model to understand what decision-makers feel contributes to decision quality. The proposed model addressed several gaps existing in the extant literature. There is not general agreement on how or why some individuals find success in using decision support technology, and why others encounter failure.

In an attempt to explain this inconsistency, many researchers use experiments which contain the “right” answer which enables decision quality to be measured objectively. However, right or correct answers are rarely known in the business world and there isn’t a standard way to measure the difference between the correct answer and the answer which was selected. As a result, these studies lack relevance to what is actually occurring in the business world. This study makes an attempt to include that subjective realism by using attribution theory to ensure the focus on the individual decision-makers. The research method reflects this as well; the survey prompts the decision makers to think of a specific decision as supported by decision support technology which yields a variety of decisions and situations.

To test the proposed hypotheses, this study examined the relationships using quantitative methods. A two-phased approach was used; the pilot tested the measurement model and the primary study tested the measurement model and evaluated the structural model allowing for the study's findings.

The results support the proposed model which is grounded in attribution theory. The perception of decision quality is significantly explained by the degree to which the decision-maker feels their task is supported by the decision support technology as well as their self-efficacy with making decisions and with using decision support technologies. The personality trait intolerance for ambiguity was shown to significantly impact the decision-maker's confidence level of making decisions and using the decision support technology.

Finally, this study provided several contributions, articulated limitations which could be used as input to future research and specified further areas of potential future research. This research can be used as input to business professionals as well as to other researchers to further our understanding of how decision quality perceptions are formed.

In summary, this research sought to understand the elements decision-makers perceive as contributing to decision quality. Holding the decision-maker's point-of-view was critical to ensure that the model, measurement, and evaluation focused on how the decision-maker observes and thinks about the decision-making process and the outcomes. This approach is in contrast to many published studies which use an assumption of a "correct" answer which can be used as a baseline to measure a respondent's decision correctness as opposed to leveraging observation and experience.

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Appendices

APPENDIX A

Items by Construct

Table 17

Items by Construct

		Pilot	Primary Study
Decision Quality			
DQ1	I believe I chose the best solution.	X	
DQ2	I believe I have selected the right option.	X	X
DQ3	I believe I selected the right solution.	X	X
DQ4	I believe I picked a solution that was good enough.	X	X
DQ5-R	I believe I made a poor decision.	X	X
DQ6	I believe I did not select the worst decision.	X	
Self-Efficacy with Decision-Making			
SEDM1	I have the ability to make a decision.	X	
SEDM2	I am highly capable of making a decision.	X	X
SEDM3	I am confident I can make a decision.	X	X
SEDM4-R	I doubt I can make a choice.	X	
SEDM5-R	I am unsure I can make a decision.	X	X
SEDM6-R	I am very uncertain whether I can make a decision (Chen et al., 2001).	X	
SEDM7	When facing difficult decisions, I am certain that I will be able to make them (Chen et al., 2001).		X
SEDM8	I am confident that I can perform effectively on many different decision tasks (Chen et al., 2001).		X
SEDM9	Even when things are tough, I can perform decision-making quite well (Chen et al., 2001).		X

Self-Efficacy with the DSS			
SEDSS1	I believe I can successfully use a decision support technology to make a decision	X	
SEDSS2	I believe I can adequately operate a decision support technology.	X	X
SEDSS3	I am confident I can successfully work with a decision support technology.	X	X
SEDSS4-R	I am unsure whether I can work with a decision support technology.	X	X
SEDSS5-R	I doubt I have the ability to use a decision support technology.	X	
SEDSS6	I could complete my job using the decision support technology if there was no one around to tell me what to do (Compeau & Higgins, 1995).		X
SEDSS7	I could complete my job using the decision support technology if I had never used a package like it before (Compeau & Higgins, 1995).		X
SEDSS8	I could complete my job using the decision support technology if I had only the software manuals for reference (Compeau & Higgins, 1995).		X
SEDSS9	I could complete my job using the decision support technology if I could call someone for help if I got stuck (Compeau & Higgins, 1995).		X
SEDSS10	I could complete my job using the decision support technology if someone else had helped me get started (Compeau & Higgins, 1995).		X
SEDSS11	I could complete my job using the decision support technology if someone showed me how to do it first (Compeau & Higgins, 1995).		X
Task-Technology Fit			
TTF1	I believe there is a good match between the decision I've made and the decision support technology.	X	X
TTF2	I believe there is an excellent fit between the decision I've made and the decision support technology.	X	X
TTF3-R	I believe there is a poor fit between the decision I've made and the decision support technology.	X	
TTF4-R	I believe there is a mismatch between the decision I've made and the decision support technology.	X	X
TTF5-R	I believe the decision support technology is not well-suited for the decision I made.	X	X
Intolerance for Ambiguity			
IAMBIG1	I am threatened by puzzling information.	X	X
IAMBIG2	I am indecisive when facing unclear information.	X	X
IAMBIG3	I am intimidated by perplexing information.	X	X
IAMBIG4	I see a risk when I encounter puzzling information.	X	X
IAMBIG5-R	I am decisive when information is straightforward.	X	

IAMBIG6-R	I perceive certainty when information is clear.	X	
IAMBIG7	I believe that clear information is desirable		X

APPENDIX B

Pilot Survey

Online Survey Consent Form

You are being invited to take part in a research study conducted by Bethany Niese of Kennesaw State University (706-864-1974, Bniese@students.kennesaw.edu). Before you

and risks of using technology to support decision making in business. There will be no partial credit for partial participation. Upon the completion of the survey you will be asked to provide your university ID number. Your number will only be used in processing of the extra credit points. Your ID is not linked to your responses to the survey.

Your responses will go a long way towards enabling us to understand better approaches to improving decision quality when using technology that will help with future decisions and technology choices.

Confidentiality

All information you provide will be kept absolutely confidential, will be accessible only to the researchers, and analyzed in the aggregate. We will take all necessary precautions to ensure the confidentiality of your responses.

Inclusion Criteria for Participation

You must be 18 years of age or older to participate in this study.

Use of Online Survey

Your device's Internet Protocol address will NOT be collected. Any identifying data is collected solely for the purpose of aggregating results and will not be shared with any third parties.

Research at Kennesaw State University that involves human participants is carried out under the oversight of an Institutional Review Board. Questions or problems regarding these activities should be addressed to the Institutional Review Board, Kennesaw State University, 585 Cobb Avenue, KH3417, Kennesaw, GA 30144-5591, (470) 578-6407.

PLEASE PRINT A COPY OF THIS CONSENT DOCUMENT FOR YOUR RECORDS, OR IF YOU DO NOT HAVE PRINT CAPABILITIES, YOU MAY CONTACT THE RESEARCHER TO OBTAIN A COPY.

If you have any questions or concerns about this study, please contact us at:

Bethany Niese, ABD

Information Systems Instructor, Computer Science and Information Systems Department

Mike Cottrell College of Business

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svaezi@kennesaw.edu;

- O I agree and give my consent to participate in this research project. I understand that participation is voluntary and that I may withdraw my consent at any time without penalty. (1)

- O I do not agree to participate and will be excluded from the remainder of the questions. (2)

Participants who select "No I do not agree to participate" will immediately exit the survey. Participants who select "Yes I agree to participate" will be directed to complete the survey below:

The intent of the first set of questions is to gather demographic information. As a reminder, the decision support tool we used during the in-class activity was Excel.

How many years of experience do you have with the decision support technology?

- O Less than 1 year (1)
- O 1 - 2 years (2)
- O 2.5 - 5 years (3)
- O 5.5 years - 7 years (4)
- O Over 7 years (5)

What is your current age?

- O Under 18 years old (1)
- O 18 - 24 years old (2)
- O 25 - 34 years old (3)
- O 35 - 44 years old (4)
- O 45 - 54 years old (5)
- O 55 - 65 years old (6)
- O Over 65 years old (7)

To which gender do you most identify?

- O Male (1)
- O Female (2)
- O Transgender Male (3)
- O Transgender Female (4)
- O Not Listed (5)
- O Prefer not to answer (6)

The next sections ask you to rate your agreement with various statements. As a reminder, the decision support tool we used during the in-class activity was Excel. The decision context is referred to in some of the statements. Decision context is defined as an understanding of the goals, tasks, issues, and opportunities that define business needs surrounding the decision task.

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I have the ability to make a decision. (SEDM1)	O	O	O	O	O	O	O
I am threatened by puzzling information. (IAMBIG1)	O	O	O	O	O	O	O
I believe I chose the best solution. (DQ1)	O	O	O	O	O	O	O
I believe I can successfully use a decision support technology to make a decision. (SEDSS1)	O	O	O	O	O	O	O
I believe there is a good match between the decision I've made and the decision support technology. (TTF1)	O	O	O	O	O	O	O
I make business decisions frequently. (FREQ)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am very uncertain whether I can make a decision. (SEDM6-R)	O	O	O	O	O	O	O
I perceive certainty when information is clear. (IAMBIG6-R)	O	O	O	O	O	O	O
I believe I did not select the worst decision. (DQ6)	O	O	O	O	O	O	O
I doubt I have the ability to use a decision support technology. (SEDSS5-R)	O	O	O	O	O	O	O
I believe the decision support technology is not well-suited for the decision I made. (TTF5-R)	O	O	O	O	O	O	O
I have a good understanding of the goal of the decision task. (CONTEXT1)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am highly capable of making a decision. (SEDM2)	O	O	O	O	O	O	O
I am indecisive when facing unclear information. (IAMBIG2)	O	O	O	O	O	O	O
I believe I have selected the right option. (DQ2)	O	O	O	O	O	O	O
I believe I can adequately operate a decision support technology. (SEDSS2)	O	O	O	O	O	O	O
I believe there is an excellent fit between the decision I've made and the decision support technology. (TTF2)	O	O	O	O	O	O	O
I have a good understanding of the tasks involved with the decision. (CONTEXT2)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am unsure I can make a decision. (SEDM5-R)	O	O	O	O	O	O	O
I am decisive when information is straightforward. (IAMBIG5-R)	O	O	O	O	O	O	O
I believe I made a poor decision. (DQ5-R)	O	O	O	O	O	O	O
I am unsure whether I can work with a decision support technology. (SEDSS4-R)	O	O	O	O	O	O	O
I believe there is a mismatch between the decision I've made and the decision support technology. (TTF4-R)	O	O	O	O	O	O	O
I have a good understanding of the issues surrounding the decision. (CONTEXT3)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am confident I can make a decision. (SEDM3)	O	O	O	O	O	O	O
I am intimidated by perplexing information. (IAMBIG3)	O	O	O	O	O	O	O
I believe I selected the right solution. (DQ3)	O	O	O	O	O	O	O
I am confident I can successfully work with a decision support technology. (SEDSS3)	O	O	O	O	O	O	O
I believe there is a poor fit between the decision I've made and the decision support technology. (TTF3-R)	O	O	O	O	O	O	O
I have a good understanding of the opportunities related to this issue. (CONTEXT4)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I doubt I can make a choice. (SEDM4-R)	O	O	O	O	O	O	O
I see a risk when I encounter puzzling information. (IAMBIG4)	O	O	O	O	O	O	O
I believe I picked a solution that was good enough. (DQ4)	O	O	O	O	O	O	O

APPENDIX C

Class Activity Prior to Pilot & Pilot Decision Tool

The research survey references a hands-on activity which is normally a part of class. The steps below highlight how the activity was executed as well as how the survey was distributed.

Activity Details

1. Prior to the lab, the instructor posted the decision-making Excel tool to the online learning management system used by the university. The students were instructed to download the file at the beginning of class.
2. The instructor and the class reviewed and completed the decision task shown in Figure 3 so that the students understood the functionality of the tool. The steps below highlight details regarding the instructor-led conversation.
    a. The instructor framed the decision; that it's each student's responsibility to choose a major. The various inputs were described then each student determined the inputs based on their own preferences. The inputs came from an existing tool which was obtained through a decision-making website.
    b. After inputting the data, each student was instructed to enter their choice in cell C18 to ensure a firm decision had been made.
    c. The instructor led a conversation regarding the value of using technology to support decisions.
3. Once the decision in Figure 3 had been made and discussion was completed, the instructor asked the students to open the next decision as shown in Figure 4.
    a. The class was instructed to complete this tab individually and ask questions if needed.
    b. Each student was to again articulate their decision on the sheet.
    c. The instructor led a conversation regarding the value of using technology to support decisions.

Post-Activity Details

1. The students were informed that they had two ways to earn the ten points of extra credit, both in reference to the activity which was just completed in class. The ten points was in addition to the 1,000 points already planned for the class, therefore it represented about 1% of the overall class grade.
    a. Option 1: Participate in the study which involves clicking a link to an online survey and completing the survey.
    b. Option 2: Write a 1-page paper on the benefits and risks of using technology to support decision-making such as in the example we just completed in class. Times New Roman, 12-point font, double-spaced
2. If the first option is chosen, they were instructed to navigate to tab "(3) Survey" which contained a link to the survey.
    a. Once the survey was completed, a separate survey opened instructing them to enter their email addresses. This step will allowed the researchers

to know who completed the exercise so that credit can be given, but could not be tied to or in any way associated with their survey responses.

b. Once the students submitted their email address, they were able to leave class.

3. If the second option was chosen, they were informed how to submit their completed document.
4. If students choose not to complete either option, they were dismissed with no negative consequences.

Decision Making Tool *Helps you make the best quality decisions.*

How To Use:
(1) The decision you are evaluating is in E5.
(2) The possible decisions are in E7 - M7.
(3) The Decision Attributes are in B9 - B13.
(4) For each Decision Attribute, enter the appropriate Value in E9:M13 (legend is in G15). All have been entered for you except for E11 - M11. **Fill in E11 - M11 in based on your own beliefs.**
(5) **Rank the Decision Attributes** [3 through 1] in C9 - C13. See legend in row 15 for score values.
(6) Consider the final Scores (E6 - M6)
(7) Enter your decision in C18.

A score will appear above each Option. The Option with the highest score should be considered the most desirable choice.

	(A) Decision to Evaluate	**Undergraduate Specialization**				
	Score	0	0	0	0	0
	(D) Options	**Information Systems**	**Business Analytics**	**Accounting**	**Supply Chain**	**Individualized Business**
(B) Decision Attributes	**(C) Rank**	(E) Meets Need?	(E) Meets Need?	(E) Meets Need?	(E) Meets Need?	(E) Meets Need?
Full-Time Salary		3	3	3	2	2
Number of Opportunities		3	3	3	3	2
Love for the Content						
Flexibility of Which Classes I Take		1	2	2	2	3
Advancement Opportunities		3	3	2	3	1

Rank: 3 = very important | 2 = pretty important | 1 = important

Meets Need? 3 = very true | 2 = true | 1 = fairly well | 0 = not at all

My Recommendation and short logical reason:

Figure 3: Pilot Decision Tool Initial Decision Task

Idea Sandbox: Decision Making Tool *Helps you make the best quality decisions.*

How To Use:
(1) The decision you are evaluating is in E5.
(2) The possible decisions are in E7 - M7.
(3) The Decision Attributes are in B9 - B13.
(4) For each Decision Attribute, enter the appropriate Value in E9:M13; the legend is in G15. All have been entered for you but **you may modify them as you see fit.**
(5) **Rank the Decision Attributes** [3 through 1] in C9 - C13. See legend in row 15 for score values.
(6) Consider the final Scores (E6 - M6)
(7) Enter your decision in C18.

A score will appear above each Option. The Option with the highest score should be considered the most desirable choice.

	(A) Decision to Evaluate	**Strategic Action**				
	Score	0	0	0	0	0
	(D) Options	**Close Plant**	**Reduce Staff (Layoffs)**	**Paycuts**	**Divest Business Unit**	**Do Nothing**
(B) Decision Attributes	**(C) Rank**	(E) Level of Negative Impact	(E) Level of Negative Impact	(E) Level of Negative Impact	(E) Level of Negative Impact	(E) Level of Negative Impact
Employee Impact		3	2	2	3	1
Share Price Impact		3	2	2	2	2
Short-term Expenses		3	3	3	3	1
Long-term Expenses		1	2	2	1	3
Public Optics		3	3	2	3	1

Rank: 3 = very important | 2 = pretty important | 1 = important

Meets Need? 3 = very true | 2 = true | 1 = fairly well | 0 = not at all

Provided by Idea Sandbox | idea-sandbox.com

My Recommendation and short logical reason:

Figure 4. Pilot Decision Tool Independent Decision Task

APPENDIX D

Primary Study Survey

ONLINE SURVEY CONSENT FORM

Title of Research Study: Making Good Decisions: An Attribution Model of Decision Quality in Complex Decision Tasks

Researcher's Contact Information: Bethany Niese, 706-864-1974, bniese@students.kennesaw.edu.

Introduction

You are being invited to take part in a research study conducted by Bethany Niese of Kennesaw State University (706-864-1974, Bniese@students.kennesaw.edu). Before you decide to participate in this study, you should read this form and ask questions about anything that you do not understand.

Description of Project

This study examines patterns of technology-supported decisions and the corresponding perception of their decision quality.

Explanation of Procedures

Please help us by answering this questionnaire as candidly as you can. The questionnaire focuses on making complex decisions by using decision-support technology. There is no right or wrong answer.

Time Required

The questionnaire should take approximately 15 minutes to complete.

Risks or Discomforts

There is no foreseeable risk associated with this study. However, at any time if you feel any discomfort you may withdraw from participating in the survey.

Benefits and Compensation

Your participation will help enabling us to understand better approaches to improving decision quality when using technology that will help with future decisions and technology choices. There is no compensation for participating in this survey.

Confidentiality

All information you provide will be kept absolutely confidential, will be accessible only to the researchers, and analyzed in the aggregate. We will take all necessary precautions to ensure the confidentiality of your responses.

Inclusion Criteria for Participation

You must be 18 years of age or older to participate in this study.

Use of Online Survey

Your device's Internet Protocol address will NOT be collected. Any identifying data is collected solely for the purpose of aggregating results and will not be shared with any third parties.   Research at Kennesaw State University that involves human participants is carried out under the oversight of an Institutional Review Board.

Questions or problems regarding these activities should be addressed to the Institutional Review Board, Kennesaw State University, 585 Cobb Avenue, KH3417, Kennesaw, GA 30144-5591, (470) 578-6407.

PLEASE PRINT A COPY OF THIS CONSENT DOCUMENT FOR YOUR RECORDS, OR IF YOU DO NOT HAVE PRINT CAPABILITIES, YOU MAY CONTACT THE

RESEARCHER TO OBTAIN A COPY

If you have any questions or concerns about this study, please contact us at:

Bethany Niese ABD

Information Systems Instructor, Computer Science and Information Systems Department

Mike Cottrell College of Business, University of North Georgia, Dahlonega, GA 30597

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Associate Professor, Information Systems

College of Business, Kennesaw State University, Kennesaw, GA 30060

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O I agree and give my consent to participate in this research project. I understand that participation is voluntary and that I may withdraw my consent at any time without penalty. (1)

O I do not agree to participate and will be excluded from the remainder of the questions. (2)

Participants who select “No I do not agree to participate” will immediately exit the survey. Participants who select “Yes I agree to participate” will be directed to complete the survey below:

Please help us by answering this questionnaire as candidly as you can. There are no right or wrong answers.

Does your role include making decisions at your company?

- O Yes (1)
- O No (2)

What is your current age?

- O Under 18 years old (1)
- O 18 - 24 years old (2)
- O 25 - 34 years old (3)
- O 35 - 44 years old (4)
- O 45 - 54 years old (5)
- O 55 - 65 years old (6)
- O Over 65 years old (7)

Which best describes your current level of education?

- O High school graduate, diploma or the equivalent (1)
- O Some college credit, no degree (2)
- O Associate degree (3)
- O Bachelor's degree (4)
- O Master's degree (5)
- O Doctorate degree (6)

How many years of experience do you have with using technology to support your business decisions?

- Less than 1 year (1)
- 1 year - 2 years (2)
- 2.5 years - 5 years (3)
- 5.5 years - 7 years (4)
- Over 7 years (5)

To which gender do you most identify?

- Male (1)
- Female (2)
- Transgender Male (3)
- Transgender Female (4)
- Not Listed (5)
- Prefer not to answer (6)

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I make business decisions frequently. (FREQ)	o	o	o	o	o	o	o
When facing difficult decisions, I am certain that I will be able to make them. (SEDM7)	o	o	o	o	o	o	o
I am indecisive when facing unclear information. (IAMBIG2)	o	o	o	o	o	o	o
I am unsure whether I can work with a decision support technology. (SEDSS4-R)	o	o	o	o	o	o	o
I could complete my job using the decision support technology if there was no one around to tell me what to do. (SEDSS6)	o	o	o	o	o	o	o

I could complete my job using the decision support technology if someone else had helped me get started. (SEDSS10)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am intimidated by perplexing information. (IAMBIG3)	O	O	O	O	O	O	O
I believe I can adequately operate a decision support technology. (SEDSS2)	O	O	O	O	O	O	O
I am highly capable of making a decision. (SEDM2)	O	O	O	O	O	O	O
I could complete my job using the decision support technology if if someone showed me how to do it first. (SEDSS11)	O	O	O	O	O	O	O
I am confident that I can perform effectively on many different decision tasks. (SEDM8)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I could complete my job using the decision support technology if I had only the software manuals for reference. (SEDSS8)	O	O	O	O	O	O	O
Even when things are tough, I can perform decision-making quite well. (SEDM9)	O	O	O	O	O	O	O
I am confident I can make a decision. (SEDM3)	O	O	O	O	O	O	O
I see a risk when I encounter puzzling information. (IAMBIG4)	O	O	O	O	O	O	O
I am confident I can successfully work with a decision support technology. (SEDSS3)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am threatened by puzzling information. (IAMBIG1)	O	O	O	O	O	O	O
I believe that clear information is desirable. (IAMBIG7)	O	O	O	O	O	O	O
I could complete my job using the decision support technology if I had never used a package like it before. (SEDSS7)	O	O	O	O	O	O	O
I could complete my job using the decision support technology if I could call someone for help if I got stuck. (SEDSS9)	O	O	O	O	O	O	O
I am unsure I can make a decision. (SEDM5-R)	O	O	O	O	O	O	O

This section asks you to rate your agreement with various statements. Please think of a specific time when you made a decision by utilizing a decision-support technology, which is any software that assists you in analyzing business data to help you make business decisions. The questionnaire will ask questions regarding the details of that decision.

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I have a good understanding of the goal of the decision task. (CONTEXT1)	O	O	O	O	O	O	O
The problem that I made the decision about was complex. (COMPLEX1)	O	O	O	O	O	O	O
I believe I have selected the right option. (DQ2)	O	O	O	O	O	O	O
I believe there is a good match between the decision I've made and the decision support technology. (TTF1)	O	O	O	O	O	O	O
I believe the decision support technology is not well-suited for the decision I made. (TTF5-R)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe I selected the right solution. (DQ3)	O	O	O	O	O	O	O
I have a good understanding of the tasks involved with the decision. (CONTEXT2)	O	O	O	O	O	O	O
I believe there is an excellent fit between the decision I've made and the decision support technology. (TTF2)	O	O	O	O	O	O	O
I have a good understanding of the opportunities related to this issue. (CONTEXT4)	O	O	O	O	O	O	O
I believe I made a poor decision. (DQ5-R)	O	O	O	O	O	O	O
The decision involved a large number of variables or elements. (COMPLEX2)	O	O	O	O	O	O	O

Please rate your agreement with the following statements.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I believe there is a mismatch between the decision I've made and the decision support technology. (TTF4-R)	O	O	O	O	O	O	O
I believe I picked a solution that was good enough. (DQ4)	O	O	O	O	O	O	O
The decision depended on the interaction of different factors. (COMPLEX3)	O	O	O	O	O	O	O
I have a good understanding of the issues surrounding the decision. (CONTEXT3)	O	O	O	O	O	O	O

APPENDIX E

Primary Study Cross Loadings

Table 18

Primary Study Cross Loadings

	DQ	IAMBIG	SEDM	SEDSS	TTF
DQ2	0.840	-0.188	0.559	0.523	0.590
DQ3	0.847	-0.149	0.473	0.534	0.620
DQ4	0.719	-0.089	0.332	0.445	0.424
IAMBIG1	-0.193	0.882	-0.404	-0.268	-0.255
IAMBIG2	-0.080	0.668	-0.143	-0.219	-0.201
IAMBIG3	-0.138	0.841	-0.291	-0.221	-0.175
SEDM2	0.511	-0.260	0.852	0.542	0.432
SEDM3	0.550	-0.230	0.832	0.471	0.405
SEDM5-RC	0.253	-0.452	0.663	0.338	0.275
SEDSS2	0.542	-0.196	0.461	0.831	0.436
SEDSS3	0.581	-0.175	0.511	0.873	0.563
SEDSS4-RC	0.120	-0.474	0.303	0.443	0.191
TTF1	0.572	-0.233	0.427	0.448	0.839
TTF2	0.591	-0.214	0.385	0.524	0.853